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A cloud computing framework on demand side management game in smart energy hubs

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ABSTRACT

The presence of energy hubs in the future vision of energy networks creates an opportunity for electrical engineers to move toward more efficient energy systems. At the same time, it is envisioned that smart grid can cover the natural gas network in the near future. This paper modifies the classic Energy Hub model to present an upgraded model in the smart environment entitling "Smart Energy Hub". Supporting real time, two-way communication between utility companies and smart energy hubs, and allowing intelligent infrastructures at both ends to manage power consumption necessitates large-scale real-time computing capabilities to handle the communication and the storage of huge transferable data. To manage communications to large numbers of endpoints in a secure, scalable and highly-available environment, in this paper we provide a cloud computing framework for a group of smart energy hubs. Then, we use game theory to model the demand side management among the smart energy hubs. Simulation results confirm that at the Nash equilibrium, peak to average ratio of the total electricity demand reduces significantly and at the same time the hubs will pay less considerably for their energy bill.
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Introduction

Recently, energy consumptions growth has led researchers to suggest integrated view of energy systems with multiple energy carriers, instead of focusing on a single one. By coupling different energy infrastructures, such as natural gas and electricity networks, the integrated system aims at attaining an optimal solution instead of two sub-optimal ones [1].

The Energy Hub (EH) model and concept was proposed by Geidl for the first time [1]. In the simple definition, an EH is a multi-generation system, where various forms of energy carriers are converted, stored and distributed using a converter system such as *combined heating and power* (CHP) to meet the energy demands [1]. The studies related to the applications of EH can be categorized in two different groups. The first group dealt with financial aspects of deploying EH in residential, commercial and industrial sectors [2–11]. In [2], authors calculated required financial parameters to analyze feasibility of an energy hub plant. Determining the optimal size of elements in an energy hub consisting of CHP, auxiliary boiler, absorption chiller, battery, and heating storage have been investigated in [3]. In [4], Kienzle et al. proposed a financial valuation method for the energy hubs with conversion, storage, and demand side management (DSM) capabilities.

The second category comprises different methods of controlling and optimizing operation of an energy hub [5–10]. In [5], the optimal operation of an energy hub is investigated by applying non-linear programming. In [6], the optimization model of a residential energy hub has been presented to incorporate into automated decision making technologies. Arnold in [7] applies a model of predictive system control approach for an energy hub with respect to the loads which are completely probabilistic. Additionally, Parisio et al [8] propose a control mechanism for an energy hub based on robust optimization (RO) technique which is less sensitive to converter efficiencies. In [9], a distributed control method has been applied to a system consisting of several interconnected hubs to shape the demands by incentivizing customers. Finally, in [10], the storage level controlling of an energy hub has been developed based on responding to the energy prices. In comparison with the existing studies, we modify EH in the smart environment, and we name it a Smart Energy Hub (S.E. Hub). We also consider interaction between the S.E. Hubs in the DSM programs.

By increasing the penetration level of CHP and micro-CHP in several countries [11], and also realizing the smart grid (SG) in electrical networks, it is not farfetched to have a smart natural gas infrastructure in the near future. Therefore, the development of new methods for *demand side management* (DSM) in natural gas and electricity networks simultaneously seems imperative. Techniques used for DSM can be categorized in two different

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groups: voluntary load management programs [12–14], and direct load control [15]. Among these methods smart pricing is one of the efficient tools that can encourage users to consume electricity more wisely [16]. Recent increases in energy price make consumers to be more active in DSM programs, and to shift the energy consumption to off-peak hours for reducing their energy bills [17]. Although most of the existing studies were successful to achieve optimal solutions for the DSM, they neglect the fact that considerable portion of the consumers, especially in the industrial sectors, do not have shiftable loads in reality. This paper deals with this issue by introducing S.E. Hubs which enables consumers with must-run loads, i.e. with strict energy consumption scheduling constraints, to be active in DSM programs.

So far, most of the proposed demand response systems have been based on master-slave architecture [12–17]. Utility's energy management system (EMS) interacts with customers' EMS individually. Basically, master-slave architecture is host-address centric communication (the senders and the receivers need to know their addresses (e.g., IP address) for communication) and is good for a small scale network due to its simplicity. However, from system protection perspective, master-slave architecture for demand response has several potential drawbacks [18–20]. It is possible that home's smart meters and EMS can be compromised by cyber attackers. From scalability perspective, the maximum numbers of clients are limited by the server's capacity. Additionally, when demand response operates as an iterative process the communication latency between a master and slaves can be high. Hence, if the utility wants to deploy a large-scale demand response program, the utility's EMS server must be able to resolve the potential problems listed so far.

Motivated by mentioned drawbacks, in this paper we propose a model for utilizing the cloud computing technology, a next-generation computing paradigm, in the smart grid domain. Cloud Computing refers to manipulating, configuring, and accessing the applications online [21]. It offers online data storage, infrastructure and application [22]. Computing, software and data services can be used by end users without knowledge of the users' IP address or configuration of the systems. Cloud computing is probably the simplest and best fitted way for smart grids due to its scalable and flexible characteristics, and its capability to manage large amounts of data [23]. The utility company and customers interact through the cloud, and the functions for realizing demand response are performed in a cloud rather than in the utility's EMS. From utility's perspective, cloud appears to be an information system that takes an input from utility (e.g., the amount of power deficit), processes the information, and gives an output to utility (e.g., how much to reduce loads per customers and at which incentive price) [24–27].

In this paper we present a cloud-base architecture that embeds SG in to a cloud environment and we explore how CC can play an effective role in DSM game among a group of S.E. Hubs.

The rest of this paper is organized as follows. The S.E. Hub model is introduced and in Section 'Smart Energy Hub; definition and modeling'. In Section 'DSM in a group of S.E. Hub', DSM in a group of S.E. Hubs is modeled with three configurations and information management methods. In Section 'DSM game optimization problem', DSM game among S.E. Hubs based on CC configuration is formulated and solved by using distributed projected gradient algorithm. Simulation results and discussions are given in Section 'Simulation and discussion', the paper is concluded in Section 'Conclusion'.

Smart Energy Hub; definition and modeling

A general model of an energy hub is presented in Fig. 1 [1]. Power conversion through the hub is modeled as follows.

$$\begin{bmatrix} P^{out}_{\alpha,i} \\ P^{out}_{\beta,i} \\ \vdots \\ P^{out}_{\omega,i} \end{bmatrix} = \begin{bmatrix} C_{\alpha\alpha} & C_{\beta\alpha} & \cdots & C_{\omega\alpha} \\ C_{\alpha\beta} & C_{\beta\beta} & \cdots & C_{\omega\beta} \\ \vdots & \vdots & \ddots & \vdots \\ C_{\alpha\omega} & C_{\beta\omega} & \cdots & C_{\omega\omega} \end{bmatrix} \begin{bmatrix} P^{in}_{\alpha,i} \\ P^{in}_{\beta,i} \\ \vdots \\ P^{in}_{\omega,i} \end{bmatrix} \tag{1}$$

where $P^{in}_{\alpha,i}, P^{in}_{\beta,i}, \ldots, P^{in}_{\omega,i}$ are the input energy carriers' power of ith S.E. Hub and $P^{out}_{\alpha,i}, P^{out}_{\beta,i}, \ldots, P^{out}_{\omega,i}$ are the output energy carriers' powers, and $C_{\alpha\beta}$ denotes the coupling factor between input energy carrier α and output energy carrier β energy flow.

A simple energy hub with two inputs (electricity and natural gas) and two outputs (electrical and heating loads) is shown in Fig. 2.

The matrix equation for the above-mentioned energy hub is

$$\begin{bmatrix} P^{out}_{e,i} \\ P^{out}_{h,i} \end{bmatrix} = \begin{bmatrix} \eta_{trans.,i} & \lambda_i \eta^{e}_{chp,i} \\ 0 & \lambda_i \eta^{h}_{chp,i} + (1-\lambda_i)\eta_{boiler,i} \end{bmatrix} \begin{bmatrix} P^{in}_{e,i} \\ P^{in}_{g,i} \end{bmatrix} \tag{2}$$

where λ_i is the dispatch factor that determines the amount of natural gas dividing between the auxiliary boiler and the CHP in ith S.E. Hub. Parameters $\eta_{trans.,i}$, $\eta_{boiler,i}$ denote the efficiencies of the transformer and the auxiliary boiler, respectively. $\eta^{h}_{chp,i}, \eta^{e}_{chp,i}$ are the heating and the electrical efficiency of the CHP.

Eqs. (3) and (4) introduce new variables $P^{in}_{chp,i}$ and $P^{in}_{Boiler,i}$ to simplify (2), where $P^{in}_{CHP,i}$ and $P^{in}_{Boiler,i}$ are amount of natural gas that inputs CHP and boiler.

$$P^{in}_{chp,i} = \lambda_i P^{in}_{g,i} \tag{3}$$

$$P^{in}_{Boiler,i} = (1-\lambda_i) P^{in}_{g,i} \tag{4}$$

By using (3) and (4), Eq. (2) can be rewritten as follows.

$$\begin{bmatrix} P^{out}_{e,i} \\ P^{out}_{h,i} \end{bmatrix} = \begin{bmatrix} \eta_{trans.,i} P^{in}_{e,i} + \eta^{e}_{CHP,i} P^{in}_{CHP,i} \\ \eta^{h}_{CHP,i} P^{in}_{CHP,i} + \eta_{boiler,i} P^{in}_{Boiler,i} \end{bmatrix} \tag{5}$$

We call an energy hub a S.E. Hub, if the EH locates in the SG and equipped with smart meters for both electricity and natural gas networks with appropriate communication infrastructures (wire or wireless network).

The overall view of a simple S.E. Hub has been illustrated in Fig. 3. All exchanged messages between the smart meters and utilities are communicated through the LAN by using appropriate communication protocols such as ZigBee, Z-Wave and KNX [28].

DSM in a group of S.E. Hub

By increasing the coverage of SG in the real world, DSM programs and their implementation turn into the hot topic for electrical engineers. Researchers deal with this issue by integrating the implementation of different components such as Home Energy Management System (HEMS) [29], Building Energy Management System (BEMS) [30] and Energy consumption scheduler (ECS)

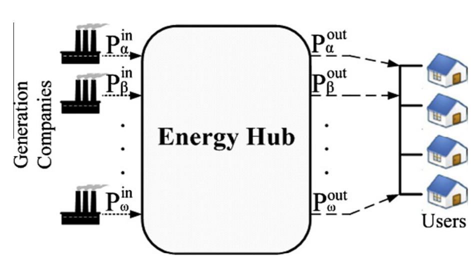

Fig. 1. The general model of an Energy Hub.

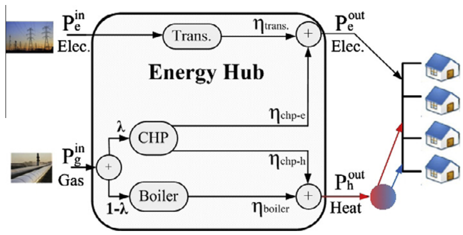

Fig. 2. The structure of a simple energy hub.

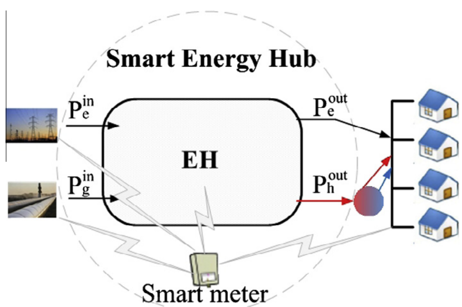

Fig. 3. The overall view of a simple S.E. Hub.

[31]. These methods can work properly in the pilot case with a few customers; however, in a system with a number of users these implementation face several problems. In this section, we provide an application of cloud computing for DSM among a group of S.E. Hubs. First, we address crucial problems in existing approaches for DSM without cloud. Then, we briefly discuss how these problems can be tackled by implementation of cloud computing. Finally, we conclude this section by proposing a cloud computing architecture.

In smart grids, users are incentivized to be active in DSM programs. There are two general actions by which a customer response to the utility companies in a regular system with single energy carrier. First, customers can reduce their electricity usage during critical peak periods when prices are high without changing their consumption pattern during other periods. This option involves a temporary loss of comfort [32]. Secondly, customers may respond to high electricity prices by shifting some of their peak demand operations to off-peak periods, as an example, they shift some household activities (e.g., dishwashers, pool pumps) to off-peak periods. However, this will not be applicable for all users, e.g., industrial loads. In this system, if a customer has only must run loads with strict energy consumption scheduling constraints, then he could not participate in the DSM program. However, if that customer deploys S.E. Hub then he could benefit from third type of DSM techniques that we are introducing in this section. In fact, coupling between different energy carriers enables customers to be active in DSM programs not only by shifting their energy consumption, but also by changing the source of their consumed energy. It enables customers to have two levels of DSM simultaneously, in both input (*level I*) and output ports (*level II*). This novel approach is not applicable in traditional smart grids with decoupled energy carrier infrastructures. However, in S.E. Hubs, customers can be active in the DSM by converting natural gas to electricity using CHPs in peak load periods instead of purchasing electricity from the electricity utility company directly. As a result, from the electricity utility's point of view, the customers do not demand electricity in peak hours; nevertheless, from the customers view point, their electricity consumption is not altered; only the source of supplying the electricity has been changed.

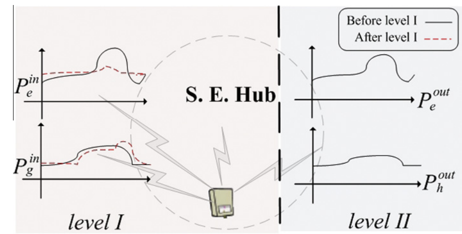

Fig. 4. Applying DSM program in the system with only must run loads.

As Fig. 4 shows, the two levels of DSM are applicable here by changing the amount of the input natural gas and electricity. Therefore, as a general result, deploying S.E. Hub can activate the customers, who do not have any roles in the DSM programs.

Now consider customers who have both must run and shiftable loads. In this case, *level I* and *level II* DSM are applicable. It means customers are able to shift their loads, and they can change their input energy carriers at the same time.

By the above considerations, in the following subsection we want to model a group of S.E. Hubs in three different configurations and investigate the DSM program in each one.

DSM based on interaction between UC and each S.E. Hub

In several DSM programs that have been deployed recently [15], the main considered factor was the interaction between UC and each customer. For instance, in real time pricing mechanisms, every customer responds to the time variant prices by shifting some shiftable loads from peak hours to the off-peak periods. As Fig. 5 demonstrates, it means each customer communicate its load profile with the UC individually.

DSM by enabling interaction between the S.E. Hubs and the UC

The proposed configuration in Fig. 5 has some disadvantages and may not always reach to the best solution of the energy consumption problem. A more efficient DSM program should have the objective to optimize and shape the aggregated load too [31]. For instance, *peak to average ratio* (PAR) only depends on aggregated load; therefore, to have more efficient DSM, the interaction among all customers should be considered. Here, natural gas and electricity utilities are shared by several S.E. Hubs, each of which is equipped with an automatic *energy consumption scheduler* (ECS) [31]. The ECS functionality is deployed inside the smart meters that are all connected to the power lines coming from the energy sources to accurately monitor the energy consumption. Each smart meter is also connected to the others smart meters through a *local area network* (LAN) as depicted in Fig. 6. The smart meters with ECS functions enable customers to figure out the best consumption strategies.

Problems with existing approaches without cloud

In the conventional smart grid architecture (without cloud) several problems are reported as follow:

- The master-slave architecture causes extensive exposure to cyber-attacks such as the distributed denial of service (DDoS) attack from the compromised nodes in the demand response model. In master-slave architecture, the utility provider acts as a master and the customers act as slaves.
- One of the main concerns in the existing approaches is single failure in master-slave architecture.
- Due to the limited server capacity the maximum number of customers who can be served is limited.

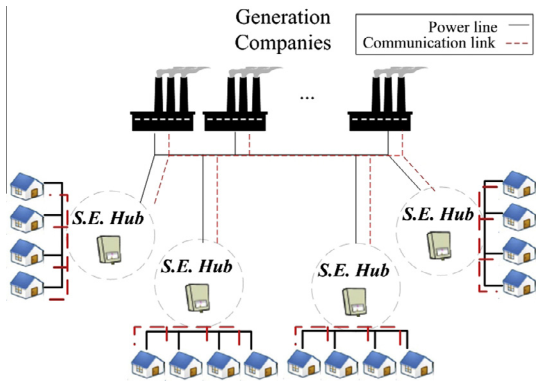

Fig. 5. Configuration A.

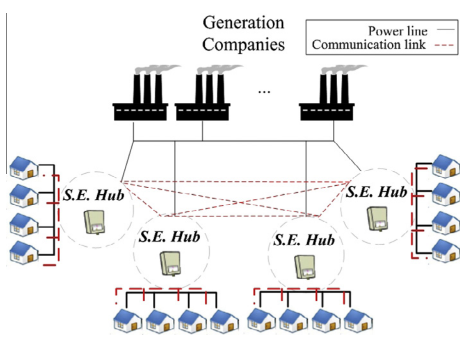

Fig. 6. Configuration B.

- Without cloud, demand response is performed in a utility's energy management systems (EMS). Because of limited memory and storage capacity, increasing the number of customers will be a crucial issue for energy management.
- In the conventional approaches (without cloud), using sensor nodes and intelligent devices, an early warning system can be integrated with the grid. However, due to limited energy and bandwidth resources, real-time implementation is quite difficult.

To address these issues cloud computing applications are one of the best methods in order to have a reliable, robust and efficient smart grid.

What is the cloud computing?

Cloud computing is an emerging computation model that provides on-demand facilities, and shared resources over the Internet. Cloud computing, based on large storage and computational devices, acts as a utility provider [33,34]. Cloud computing provides three distinct types of services — Platform as a Service (PaaS), Software as a Service (SaaS), and Infrastructure as a Service (IaaS) [35].

- *Infrastructure as a Service (IaaS):* IaaS is the infrastructure service model that includes storage and virtual machines. Load balancing in cloud computing is performed using IaaS. Users can install access to required software through virtual machines. These virtual devices provide on-demand facility to the customers. The IaaS service offers hardware platform to the users' on-demand basis. Therefore, users can access the online hardware platform as on-demand basis to fulfil their requirements. Additionally, the IaaS service also supports virtualization of resources, on which a guest user can run his/her own operating system [36].
- *Platform as a Service (PaaS):* PaaS is responsible for the development and delivery of programming models to IaaS. Users can access such programming models through cloud and execute their programs [36]. PaaS is responsible for the run-time execution of users' given task. Therefore, the PaaS service completes the requirements of building and delivering of Web-applications without downloading and installing required software as well.
- *Software as a Service (SaaS):* SaaS supports all the applications in the cloud environment. This feature of cloud computing is accessible through Web-browsers. The SaaS service provides the modeling of software deployment where users can run their applications without installing it on his/her own computer. However, this service is limited to the users, i.e., only existing set of services is available to the customers.

The advantages of using a cloud computing model are as follows:

- *Elastic Nature:* Cloud computing supports elastic nature of storage and memory devices. It can expand and reduce itself according to the demand from the users, as needed.
- *Shared Architecture:* Cloud computing also supports shared architecture. Information can be shared among the users after meeting the privacy issues, and thereby, reducing service costs [37].
- *Metering architecture:* Cloud computing offers metering infrastructure to customers [38]. In the metering system, cost optimization mechanisms are offered to users, enabling them to provision and pay for their consumed resources only.
- *Internet services:* Cloud computing can be implemented in the existing Internet service system. Thus, it supports the existing network infrastructure.

Now, by considering above benefits, we propose a new architecture of a group of S.E. Hub in the CC frame work in the next subsection.

DSM in CC framework

As we discussed previously, monitoring, metering, measurement, and control devices in SG generate extensive data. These overwhelming data need costly and scalable storage and computing infrastructure for data processing. In a previous configuration (Fig. 6) it would cause too much time spending or even beyond S.E. Hubs' capacity to implement such communication, storage, and computation systems. To overcome this impediment, we apply the CC configuration as shown in Fig. 7. By using cloud infrastructure, each S.E. Hub would access to its applications anytime, from anywhere, through a connected device to the network.

DSM game optimization problem

As game theory is an effective approach in dealing with complicated interaction, here we apply this theory to solve the DSM problem.

Game theory is the study of conflicts and cooperation among intelligent rational decision-makers [31], which has been used in smart grid [31,39–43]. In this paper, the DSM problem with multiple S.E. Hubs in the CC frame work is formulated as a non-cooperative game model. In the following, some preliminary knowledge about non-cooperative game will be given.

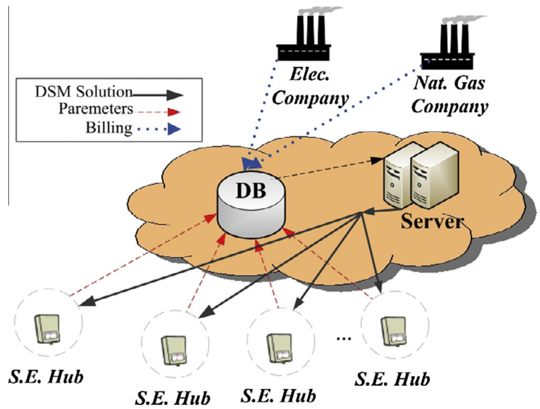

Fig. 7. Configuration C.

Preliminaries of non-cooperative game

This type of game consists of three components [43].

- Player set $N = \{1, 2, \ldots, i, \ldots, n\}$: where i is the identification of a player.
- Strategy space S: player i in a game selects strategy s_i from its strategy set S_i. $S = \times_i^n S_i$ represents strategy space of the game. Denote $s = (s_i, s_{-i})$ as the strategy vector, where s_i is the player i 's strategy, and s_{-i} represents all the other players' strategies.
- Payoff: Player i 's payoff is determined by the strategy vector s.

Nash equilibrium is the most important concept in game theory, which is a static stable strategy vector that no player has any incentive to unilaterally change its strategy from it. The definition of Nash equilibrium can be described as follows [43].

Definition 1. An strategy vector $s^* = (s_i^*, s_{-i}^*)$ is a Nash equilibrium if and only if $\forall i \in N$ and $\forall s_i \in S_i$,

$$u(s^*) \geqslant u(s_i, s_{-i}^*)$$

In particular, the existence of Nash equilibrium can be obtained according to the following lemma.

Lemma 1. If the following conditions are satisfied, there exist Nash equilibriums in the game.

- The player set is finite.
- The strategy sets are closed, bounded, and convex.
- The utility functions are continuous and quasi-concave in the strategy space.

Group of S.E. Hubs optimization problem

In general, each S.E. Hub behaves in a selfish and rational way, and aims to maximize its own payoff. Therefore, the competition among them can be modeled as a non-cooperative game.

The total energy bill cost of ith S.E. Hub in one hour is calculated as follows.

$$\begin{aligned} J_i &= J_{\alpha,i}(P^{\text{in}}_{\alpha,i}) + J_{\beta,i}(P^{\text{in}}_{\beta,i}) + \ldots + J_{\omega,i}(P^{\text{in}}_{\omega,i}) \\ &= P^{\text{in}}_{\alpha,i} \times \Pr_\alpha + P^{\text{in}}_{\beta,i} \times \Pr_\beta + \ldots + P^{\text{in}}_{\omega,i} \times \Pr_\omega \end{aligned}$$

where variable J_i is the total energy bill of the S.E. Hub in an hour and $J_{\alpha,i}, J_{\beta,i}, \ldots, J_{\omega,i}$ denote the cost of each energy carrier separately. Variables $Pr_\alpha, Pr_\beta, \ldots, Pr_\omega$ are the tariff prices for the energy carriers in (\$/kWh).

Energy carrier pricing mechanism

The energy carriers' prices should depend on the total energy consumption of the S.E. Hubs. Therefore we can consider the energy carriers' prices as follow:

$$\Pr_e = a\left[\sum_k \left(P^{\text{in}}_{e,k}\right)\right]^\alpha, \quad a = a'/G_e^\alpha \tag{6}$$

$$\Pr_g = b\left[\sum_k \left(P^{\text{in}}_{g,k}\right)\right]^\beta, \quad b = b'/G_g^\beta \tag{7}$$

The effect of nonlinear relationship between load and price is modeled by nonlinear Eqs. (6) and (7) [44,45]. Parameters a' and b' are the base tariff prices in (\$/kWh) and the available electricity and natural gas capacity are denoted by G_e and G_g as constant parameters.

DSM game modeling

Suppose all S.E. Hubs are price anticipator [44], which means they consider the effect of their actions on the price, and are know that the electricity and gas prices are calculated according to (6) and (7). Each S.E. Hub wishes to locally and selfishly choose its action in such way that minimizes its total bill cost as formulated in (6). The strategy chosen by each S.E. Hub affects the performance of others through affecting the electricity and natural gas price value. Consequently, game theory provides a natural framework for analyzing and developing proper DSM mechanisms for scheduling the consumption [39–43]. In a distributed DSM setting, each S.E. Hub attempts to minimize its own energy cost in response to the aggregated information on the actions of the other users. This makes the use of non-cooperative game theory an appropriate method to address the problem, with the relevant solution concept which is the *Nash equilibrium* (NE) [46]. In other words, if all network users selfishly and locally pick their own strategies; there will be a stable state at which no user can unilaterally improve its payoff (NE).

In the DSM game, for ith S.E. Hub, the best strategy is the solution of the following optimization problem when other users are assumed to be unchanged:

$$\begin{aligned} \min \quad & J_i = J_{e,i}(P^{\text{in}}_{e,i}) + J_{g,i}(P^{\text{in}}_{g,i}) = P^{\text{in}}_{e,i} \times \Pr_e + P^{\text{in}}_{g,i} \times \Pr_g \\ \text{s.t} \quad & P^{\text{out}}_{e,i} = \eta_{\text{trans},i} P^{\text{in}}_{e,i} + \eta^{e}_{\text{CHP},i} P^{\text{in}}_{\text{CHP},i} = L_{e,i} \\ & P^{\text{out}}_{h,i} = \eta^{h}_{\text{CHP},i} P^{\text{in}}_{\text{CHP},i} + \eta_{\text{boiler},i} P^{\text{in}}_{\text{Boiler},i} \geqslant L_{h,i} \\ & 0 \leqslant P^{\text{in}}_{\text{CHP},i} \leqslant \text{Cap}_{\text{CHP},i} \\ & 0 \leqslant P^{\text{in}}_{\text{Boiler},i} \leqslant \text{Cap}_{\text{Boiler},i} \end{aligned} \tag{8}$$

Variables $L_{e,i}$ and $L_{h,i}$ are the electricity and the heating loads, and parameters $\text{Cap}_{\text{CHP},i}$ and $\text{Cap}_{\text{Boiler},i}$ denote the capacity of CHP and boiler, respectively.

We can identify the game as follows.

- Players are S.E. Hubs, $\Gamma = \{1, 2, \ldots, N\}$.
- Strategies: each player selects its energy consumption schedule vector, $\vec{X}_i = \left(P^{\text{in}}_{\text{CHP},i}, P^{\text{in}}_{\text{Boiler},i}\right)$, to minimize its pay-off: $P^{\text{in}}_{\text{CHP},i} \in \left[0, \text{Cap}_{\text{CHP},i}\right], P^{\text{in}}_{\text{Boiler},i} \in \left[0, \text{Cap}_{\text{Boiler},i}\right]$.
- Payoffs: for every S.E. Hub, minus energy cost, i.e. payoff $= -J_i(\vec{X}_i, \vec{X}_{-i})$, where J_i is the sum of electricity and natural gas costs (6).

Here, $\vec{X}_{-i} = \left[\vec{X}_1; \ldots; \vec{X}_{i-1}; \vec{X}_{i+1}; \ldots; \vec{X}_N\right]$ denotes the vector containing the energy consumption schedules of all S.E. Hubs other than ith S.E. Hub.

Existence and uniqueness of NE

Theorem1. The optimization problem for each S.E. Hub is strictly convex.

The proof of Theorem 1 is given in Appendix A.

If the cost of each S.E. Hub is strictly convex, then the payoff function becomes strictly concave and the game will be *n*-person concave game. As Rosen in [46] proved, the Nash equilibrium of the above game exists and is unique.

The result of the game is the Nash equilibrium at which CHP and Boiler inputs vector $\vec{X}^*$ satisfies

$$J_i\left(\vec{X}_i^*, \vec{X}_{-i}^*\right) \leqslant J_i\left(\vec{X}_i, \vec{X}_{-i}^*\right) \tag{9}$$

where $\vec{X}^* = \left[\vec{X}_1^*; \vec{X}_2^*; \ldots; \vec{X}_N^*\right]$.

If the energy consumption game is at its unique Nash equilibrium, then no S.E. Hub will benefit by deviating from $\vec{X}^*$.

All required calculations to determine the Nash equilibrium are performed in the CC. Each S.E. Hub only communicates its load profile to the CC hourly. S.E. Hubs should also communicate any changes in capacities and efficiencies of its transformer ($\mathrm{Cap}_{\mathrm{trans},i}$, $\eta_{\mathrm{trans},i}$), boiler ($\mathrm{Cap}_{\mathrm{Boiler},i}$, $\eta_{\mathrm{boiler},i}$) and CHP $\left(\mathrm{Cap}_{\mathrm{CHP},i}, \eta^{\mathrm{h}}_{\mathrm{CHP},i}, \eta^{\mathrm{e}}_{\mathrm{CHP},i}\right)$, to the CC. It is worth mentioning that without using CC, S.E. Hubs have to share all these information with each other via message exchange.

Distributed projected algorithm

The above optimization problem suggests a distributed algorithm based on projected gradient method [44] to determine the Nash equilibrium. The computation is done in the CC and results will be reported to each S.E. Hub.

At 1th iteration:

Customers reports their required loads $L_{e,i}$ and $L_{h,i}$, and any changes in ($\mathrm{Cap}_{\mathrm{trans},i}$, $\mathrm{Cap}_{\mathrm{CHP},i}$, $\mathrm{Cap}_{\mathrm{Boiler},i}$, $\eta_{\mathrm{trans},i}$, $\eta_{\mathrm{boiler},i}$, $\eta^{\mathrm{h}}_{\mathrm{CHP},i}$, $\eta^{\mathrm{e}}_{\mathrm{CHP},i}$) to the CC.

At kth iteration:

Customer *i*th update $\vec{X}_i^{\mathrm{k}} = \left(P^{\mathrm{in}}_{\mathrm{CHP},i}, P^{\mathrm{in}}_{\mathrm{Boiler},i}\right)^{\mathrm{k}}_{i\in\Gamma}$ according to the following iterative equations:

$$\vec{X}_i^{\mathrm{k}+1} = \mathrm{Proj}\left\{\vec{X}_i^{\mathrm{k}} - \mu\vec{\nabla}_i^{\mathrm{k}}\right\} \tag{10}$$

where $\mathrm{Proj}(\cdot)$ is the projection on to feasible region, and $\mu > 0$ is a constant step size. In [47,48], it was shown that for small enough step size μ, this algorithm converges to optimal point. The details of the method are discussed in Appendix B. Accordingly, we can write

$$P^{\mathrm{in}}_{\mathrm{CHP},i}{}^{\mathrm{k}+1} = \mathrm{Proj}\left\{P^{\mathrm{in}}_{\mathrm{CHP},i}{}^{\mathrm{k}} - \mu.\frac{\partial J_i}{\partial P^{\mathrm{in}}_{\mathrm{CHP},i}}\right\} \tag{11}$$

$$P^{\mathrm{in}}_{\mathrm{Boiler},i}{}^{\mathrm{k}+1} = \mathrm{Proj}\left\{P^{\mathrm{in}}_{\mathrm{Boiler},i}{}^{\mathrm{k}} - \mu.\frac{\partial J_i}{\partial P^{\mathrm{in}}_{\mathrm{Boiler},i}}\right\} \tag{12}$$

Based on [47,48], the projection to the feasible region is described in Appendix C.

Simulation and discussion

In this section, numerical examples are provided for verifying the DSM game. In our benchmark system, we consider there exist $N = 10$ S.E. Hubs that are served by one power substation and one natural gas resource. We assume that each S.E. Hub has only must-run loads, i.e., with strict energy consumption scheduling constrains. All S.E. Hubs have equal daily electrical and heating loads equal to 200 kWh and 120 kWh, respectively. The electrical and heating demand in a sample day at 20:00 are shown in Figs. 8 and 9 shows the daily heating and electrical load of 5th S.E. Hub.

For the purpose of study, DSM program in two different configurations have been simulated. The first is the system without interaction among users (configuration A), and the second is the system with DSM game in CC framework (configuration C).

By applying the proposed algorithm and recursive equation in Section 'DSM game optimization problem', the DSM game among S.E. Hubs leads to the following result shown in Fig. 10.

Convergence of energy carriers' price at the sample time slot is shown in Fig. 11.

Energy carrier price

We perform the second group of simulations to evaluate the performance of the proposed method to modify power demand, energy carrier prices, and energy bill for each S.E. Hub. Firstly, to have a benchmark to compare our results with, we present a conventional system that supplies its electrical and heating loads through power grid and boiler, respectively. Note that, DSM cannot be possible in such system since the loads are must run. The daily heating and electrical load of fifth S.E. Hub are shown in Fig. 12.

When the DSM game is played (configuration C), all S.E. Hubs actively participate in this game. It means in the electricity peak hours, i.e. 18:00–23:00, they decrease the input electricity consumption and supply their loads with natural gas instead. Hence, the electricity price is reduced up to 43% (at 22:00) in the peak hours.

S.E. Hub payment

The proposed DSM game leads to less energy bill for each S.E. Hub. In Fig. 13 total daily bill before and after playing the game for 5th S.E. Hub is depicted. From Fig. 13 participating in the DSM game results considerable reduction in the S.E. Hub's total energy bill cost. The daily total energy bill cost was 16.6 $ and has been reduced to 11.8 (i.e. 28.9%) after running the defined game.

Comparing peak to average ratio

The proposed DSM game leads to less S.E. Hubs payment; it is also beneficial for the electricity grid by reducing the PAR in the aggregated load demand. The PAR for energy carrier α is calculated as follows.

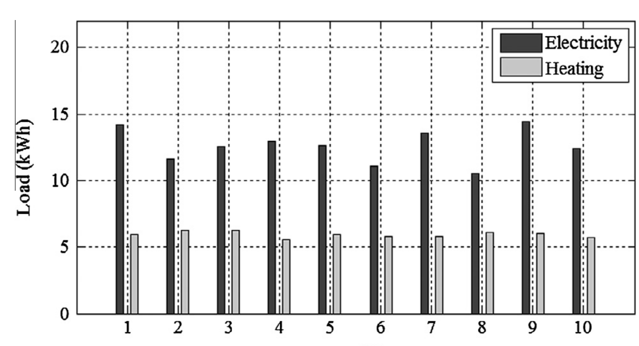

Fig. 8. Electricity and heating demands of various users at a sample time slot.

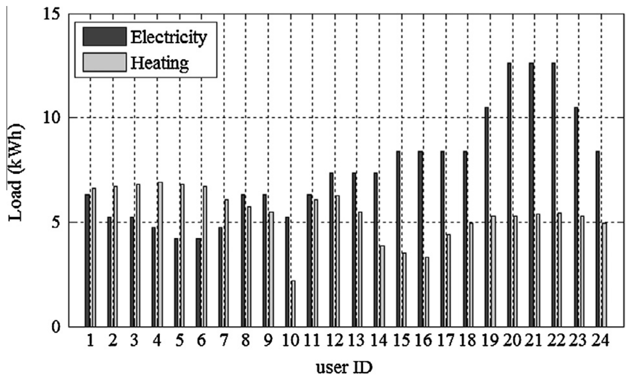

Fig. 9. Daily heating and electrical loads of the fifth S.E. Hub.

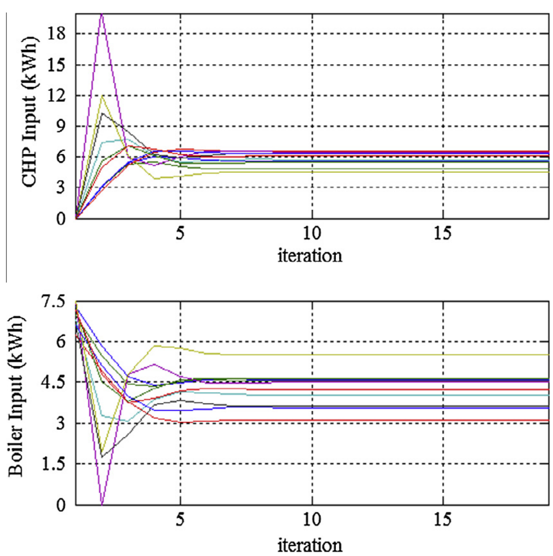

Fig. 10. Convergence of CHPs and boilers inputs for 10 S.E. Hubs (sample time slot).

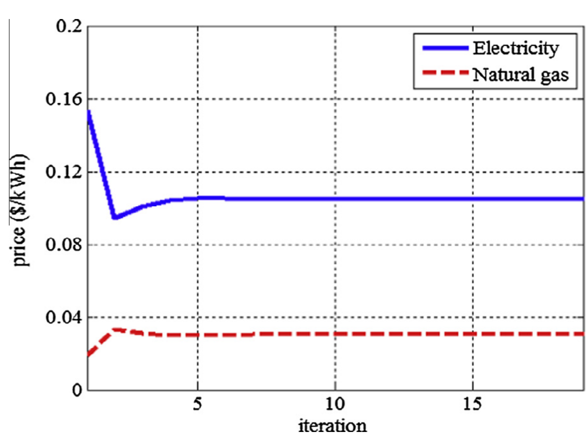

Fig. 11. Energy-carriers prices in a sample time slot.

$$
\mathrm{PAR} = \frac{\max\limits_{t=1,2,\ldots,24} P_{\alpha}^{\mathrm{in}}(t)}{\sum_{t=1,2,\ldots,24} P_{\alpha}^{\mathrm{in}}(t)/24} \tag{13}
$$

When the S.E. Hubs do not participate in the DSM game, the PAR is 1.66 and 1.28 for the electricity and natural gas, respectively. At the same condition, when they are price anticipating and play in the DSM game, the PAR for electricity grid reduces to 1.45 (i.e., 13% less)

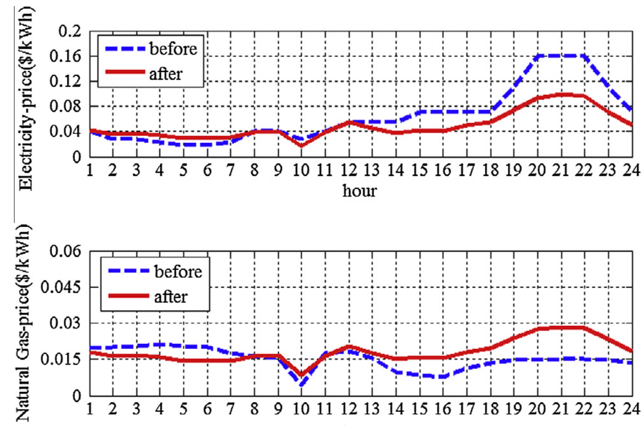

Fig. 12. Energy prices in a day hours.

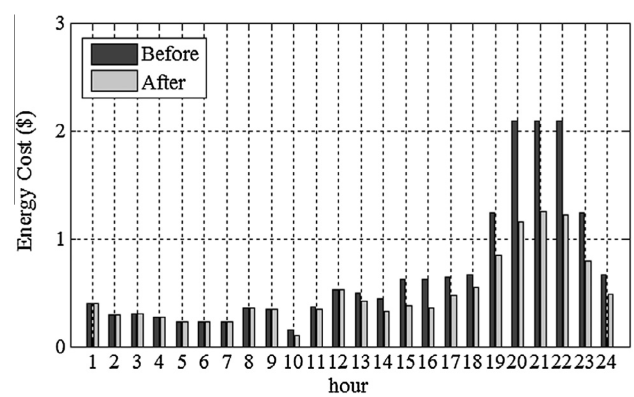

Fig. 13. Total daily cost before and after playing the game for the fifth S.E. Hub.

and increases to 1.39 (i.e. 8% more) for natural gas grid, respectively. Fig. 14 shows the aggregated electricity and natural gas load demand with and without DSM game.

Communication requirement for the proposed configuration

As it was discussed before, sharing the minimum requisite data of the S.E. Hub is one of the significant features of using CC. In this subsection, the exchanged messages size (total bytes) between S.E. Hubs is considered as another indication to compare the proposed configuration with a system which has regular interaction among all the S.E. Hubs. In the proposed configuration, each S.E. Hub is asked to submit its parameters to the CC every day. Note that, each parameter occupies 4 bytes memory. In return, the CC determines the payment and the allocated power of each S.E. Hub by solving the game according to the cost functions.

In practice, it may be preferable for the S.E. Hubs to communicate only with a trusted CC instead of sharing total load profile with each other. In a regular system that they have to interact with others, to determine Nash equilibrium, each S.E. Hub informs the others whenever it changes its power consumption. The message is sent every time that one of the S.E. Hubs updates its power consumption information.

The average size of messages exchanged in one day (24 h) between various users in the proposed configuration, and the regular one are presented in Table 1. As illustrated in Table 1, the regular method requires much more messages size, and processing time comparing with CC framework.

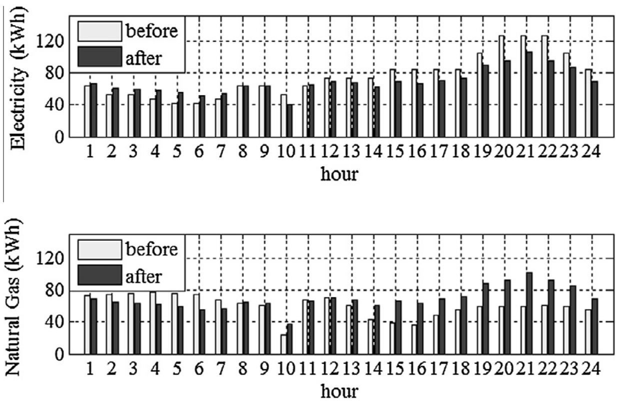

Fig. 14. Total electricity and natural gas demands before and after DSM game.

Table 1
Comparing exchanged messages' average size (total bytes) data in the regular and CC configuration.

Number of S.E. Hubs	Exchanged messages' size (Byte)	
	Config. B	Config. C
2	9600	768
5	96,000	1920
10	432,000	3840
20	1,824,000	7680
30	4,176,000	11,520

The operational cost in the proposed configuration

As we discussed in the previous sections, the sophistication of the SG may lead to a highly complex information management system. For traditional electric utilities, realizing such complicated information systems may be costly or even beyond their capacity. Therefore, it would be a good option to get the information technology sector involved and outsource some tasks to the clouds, which provide cost-effective computing and storage solutions.

Here for comparing configurations B and C, the two terms of operational cost are calculated: network cost and cloud service cost.

Networking providers own the communications and network infrastructure, and provide the information transmission. Therefore, they receive the cost of their service from S.E. Hubs for each bytes of data transmission.

The cloud managers provide storage and computing services. Each cloud manager has one pricing policy (including transfer-in, transfer-out, storage, and computation pricing), while different clouds may have different pricing policies. Here for simplicity, it is assumed that we should pay a constant payment for renting a sufficient cloud service for each S.E. Hub in a month [49].

If the cost of data transmission and cloud service are 5 cents/kByte and 50 $/(month hub) [49] respectively, the total operational cost is computed as Table 2 in one year for 10 S.E. Hubs.

As we see, the total cost is reduced by using proposed configuration. It is noteworthy that if the number of S.E. Hubs is increased, the proposed configuration becomes more economical. The costs, benefits, and net present worth of adopting configuration C in comparisons with B are illustrated in Fig. 15.

Table 2
Comparing operational cost in regular and CC configuration.

	Config. B	Config. C
Message exchange cost ($)	7884	70.08
Cloud service cost ($)	0	6000
Total cost ($)	7884	6070.08

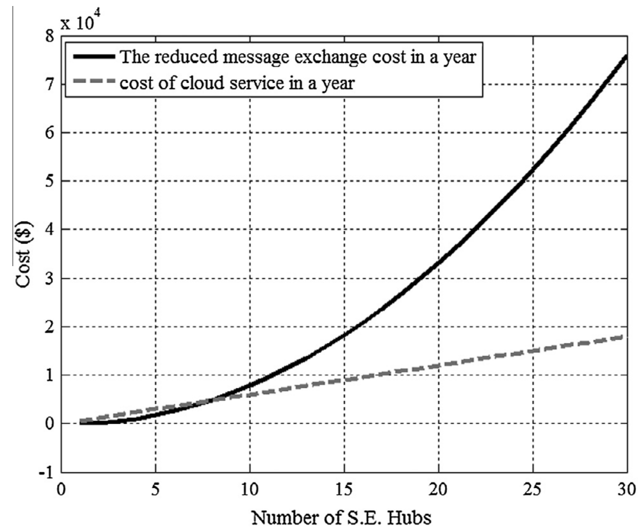

Fig. 15. The costs of adopting proposed configuration.

Conclusion

In this study, we have introduced Smart Energy Hub (S.E. Hub), which is an Energy Hub (EH) in smart grid environment. Then, we described how this system can enable users with must run loads to participate in DSM program. To facilitate the information management among a group of S.E. Hubs we proposed a new configuration based on cloud computing (CC) system. In this model, S.E. Hubs communicate their load profiles to the CC to reach an optimal DSM based on the game theoretic approach. The result of the game leads to a proper strategy for each S.E. Hub to minimize their energy bill. The projected sub gradient optimization method is applied to achieve the NE, and the existence and uniqueness of it has been proved. To evaluate the proposed method, a benchmark with ten S.E. Hubs has been investigated. Simulation results confirm that the proposed DSM game can reduce the PAR in electricity grid. In addition, the daily energy charges of each S.E. Hub have been reduced significantly. Finally, while our analysis focused only on simulation results of S.E. Hub, in future studies, we can consider a real world case and endorse simulation results with that.

Appendix A

To prove the convexity, the feasible set and the objective function have to be convex.

The answer feasible set of optimization problem is:

$$\begin{aligned} &\mathrm{L}_{\mathrm{h},i} \leqslant P^{\mathrm{out}}_{\mathrm{h},i} = \eta^{\mathrm{h}}_{\mathrm{CHP},i} P^{\mathrm{in}}_{\mathrm{CHP},i} + \eta_{\mathrm{boiler},i} P^{\mathrm{in}}_{\mathrm{Boiler},i} \\ &0 \leqslant P^{\mathrm{in}}_{\mathrm{CHP},i} \leqslant \mathrm{Cap}_{\mathrm{CHP},i} \\ &0 \leqslant P^{\mathrm{in}}_{\mathrm{Boiler},i} \leqslant \mathrm{Cap}_{\mathrm{Boiler},i} \end{aligned} \tag{A.1}$$

The feasible combination set of $P^{\mathrm{in}}_{\mathrm{CHP},i}$ and $P^{\mathrm{in}}_{\mathrm{Boiler},i}$ is convex.

The objective function is

$$J_i = J_{\mathrm{e},i} + J_{\mathrm{g},i} = P^{\mathrm{in}}_{\mathrm{e},i} \times \mathrm{Pr}_{\mathrm{e}} + P^{\mathrm{in}}_{\mathrm{g},i} \times \mathrm{Pr}_{\mathrm{g}} \tag{A.2}$$

If the hessian matrix of the objective function is positive definite, the function will be strictly convex.

By using the hessian of the summation and multiplication, we have

$$\nabla^2(f_1\times g_1+f_2\times g_2)=\left\{g_1\times\nabla^2 f_1+f_1\times\nabla^2 g_1+(\nabla f_1)\times(\nabla g_1^{\mathrm{T}})+\left(\nabla g_1\right)\times(\nabla f_1^{\mathrm{T}})\right\}+\left\{g_2\times\nabla^2 f_2+f_2\times\nabla^2 g_2+\left(\nabla f_2\right)\times(\nabla g_2^{\mathrm{T}})+(\nabla g_2)\times(\nabla f_2^{\mathrm{T}})\right\} \quad (A.3)$$

The differentiation and hessian of elements of (A.2) are as below.

$$\nabla P^{\mathrm{in}}_{\mathrm{e},i}=\begin{bmatrix}\frac{\partial P^{\mathrm{in}}_{\mathrm{e},i}}{\partial P^{\mathrm{in}}_{\mathrm{CHP},i}}\\ \frac{\partial P^{\mathrm{in}}_{\mathrm{e},i}}{\partial P^{\mathrm{in}}_{\mathrm{Boiler},i}}\end{bmatrix}=\begin{bmatrix}-\eta^{\mathrm{e}}_{\mathrm{CHP},i}\\ 0\end{bmatrix} \quad (A.4)$$

$$\nabla P^{\mathrm{in}}_{\mathrm{g},i}=\begin{bmatrix}\frac{\partial P^{\mathrm{in}}_{\mathrm{g},i}}{\partial P^{\mathrm{in}}_{\mathrm{CHP},i}}\\ \frac{\partial P^{\mathrm{in}}_{\mathrm{g},i}}{\partial P^{\mathrm{in}}_{\mathrm{Boiler},i}}\end{bmatrix}=\begin{bmatrix}1\\ 1\end{bmatrix} \quad (A.5)$$

$$\nabla^2 P^{\mathrm{in}}_{\mathrm{e},i}=\nabla^2 P^{\mathrm{in}}_{\mathrm{g},i}=0 \quad (A.6)$$

$$\nabla \mathrm{Pr_e}=\begin{bmatrix}\frac{\partial \mathrm{Pr_e}}{\partial P^{\mathrm{in}}_{\mathrm{CHP},i}}\\ \frac{\partial \mathrm{Pr_e}}{\partial P^{\mathrm{in}}_{\mathrm{Boiler},i}}\end{bmatrix}=\begin{bmatrix}-\eta^{\mathrm{e}}_{\mathrm{CHP},i}a\alpha\left[\sum_{\mathrm{k}}(P^{\mathrm{in}}_{\mathrm{e,k}})\right]^{\alpha-1}\\ 0\end{bmatrix} \quad (A.7)$$

$$\nabla \mathrm{Pr_g}=\begin{bmatrix}\frac{\partial \mathrm{Pr_g}}{\partial P^{\mathrm{in}}_{\mathrm{CHP},i}}\\ \frac{\partial \mathrm{Pr_g}}{\partial P^{\mathrm{in}}_{\mathrm{Boiler},i}}\end{bmatrix}=\begin{bmatrix}b\beta\left[\sum_{\mathrm{k}}\left(P^{\mathrm{in}}_{\mathrm{g,k}}\right)\right]^{\beta-1}\\ b\beta\left[\sum_{\mathrm{k}}\left(P^{\mathrm{in}}_{\mathrm{g,k}}\right)\right]^{\beta-1}\end{bmatrix} \quad (A.8)$$

$$\nabla^2 \mathrm{Pr_e}=\begin{bmatrix}\eta^{\mathrm{e}}_{\mathrm{CHP},i}{}^2 a\alpha(\alpha-1)\left[\sum_{\mathrm{k}}\left(P^{\mathrm{in}}_{\mathrm{e,k}}\right)\right]^{\alpha-2} & 0\\ 0 & 0\end{bmatrix} \quad (A.9)$$

$$\nabla^2 \mathrm{Pr_e}=b\beta(\beta-1)\left[\sum_{\mathrm{k}}\left(P^{\mathrm{in}}_{\mathrm{g,k}}\right)\right]^{\beta-1}\begin{bmatrix}1 & 1\\ 1 & 1\end{bmatrix} \quad (A.10)$$

By doing some algebraic computation, the hessian matrix of objective function becomes

$$\nabla^2 J_i=\begin{bmatrix}A+B & B\\ B & B\end{bmatrix}$$

$$A=\eta^{\mathrm{e}}_{\mathrm{CHP},i}{}^2 a\alpha(\alpha-1)\left[\sum_{\mathrm{k}}\left(P^{\mathrm{in}}_{\mathrm{e,k}}\right)\right]^{\alpha-2}+2\eta^{\mathrm{e}}_{\mathrm{CHP},i}{}^2 a\alpha\left[\sum_{\mathrm{k}}\left(P^{\mathrm{in}}_{\mathrm{e,k}}\right)\right]^{\alpha-1}$$

$$B=b\beta(\beta-1)\left[\sum_{\mathrm{k}}\left(P^{\mathrm{in}}_{\mathrm{g,k}}\right)\right]^{\beta-1}+2b\beta\left[\sum_{\mathrm{k}}\left(P^{\mathrm{in}}_{\mathrm{g,k}}\right)\right]^{\beta-1} \quad (A.11)$$

If α, $\beta > 1$, all of principal minors become positive. Therefore, the hessian matrix is positive definite.

Appendix B

To solve constraint optimization problem

$$\begin{array}{ll}\min & f(x)\\ \text{s.t.} & x\in C\end{array} \quad (B.1)$$

where $f{:}R^{\mathrm{n}}\rightarrow R^{\mathrm{n}}$ and $C\subseteq R^{\mathrm{n}}$ are convex. The projected gradient method is given by

$$\vec{X}^{\mathrm{k}+1}=\mathrm{Proj}\left(\vec{X}^{\mathrm{k}}-\lambda\vec{g}^{\mathrm{k}}\right) \quad (B.2)$$

Proj(·) is projection on C, and $\vec{g}^{\mathrm{k}}=\nabla f\left(\vec{X}\mathrm{k}\right)$. For linear equality constraints $A\vec{X}=b$ projection of z onto $\left\{\vec{X}|A\vec{X}=b\right\}$ is

$$\mathrm{Proj}(z)=z-A^{\mathrm{T}}\left(AA^{\mathrm{T}}\right)^{-1}(Az-b)=\left(I-A^{\mathrm{T}}\left(AA^{\mathrm{T}}\right)^{-1}A\right)z+A^{\mathrm{T}}\left(AA^{\mathrm{T}}\right)^{-1}b \quad (B.3)$$

Projected sub gradient update is

$$\vec{X}^{\mathrm{k}+1}=\mathrm{Proj}\left(\vec{X}^{\mathrm{k}}-\lambda\vec{g}^{\mathrm{k}}\right)=\vec{X}^{\mathrm{k}}-\lambda\left(I-A^{\mathrm{T}}\left(AA^{\mathrm{T}}\right)^{-1}A\right)\vec{g}^{\mathrm{k}} \quad (B.4)$$

For inequality constraints $a^{\mathrm{T}}x\geqslant b$, we have

$$\mathrm{Proj}(x)=\begin{cases}x+\frac{b-a^{\mathrm{T}}x}{\|a\|_2^2}a & \text{if } a^{\mathrm{T}}x<b\\ x & \text{otherwise}\end{cases} \quad (B.5)$$

Appendix C

At kth iteration:

Customers ith update $\vec{X}^{\mathrm{k}}_i=\left(P^{\mathrm{in}}_{\mathrm{CHP},i},P^{\mathrm{in}}_{\mathrm{Boiler},i}\right)^{\mathrm{k}}_{i\in\Gamma}$ according to the following iterative equations.

$$P^{\mathrm{in}}_{\mathrm{CHP},i}{}^{\mathrm{k}+1}=\mathrm{Proj}\left\{P^{\mathrm{in}}_{\mathrm{CHP},i}{}^{\mathrm{k}}-\mu.\frac{\partial J_i}{\partial P^{\mathrm{in}}_{\mathrm{CHP},i}}\right\} \quad (C.1)$$

$$P^{\mathrm{in}}_{\mathrm{Boiler},i}{}^{\mathrm{k}+1}=\mathrm{Proj}\left\{P^{\mathrm{in}}_{\mathrm{Boiler},i}{}^{\mathrm{k}}-\mu.\frac{\partial J_i}{\partial P^{\mathrm{in}}_{\mathrm{Boiler},i}}\right\} \quad (C.2)$$

The projection is based on the following equations.

$$\mathrm{Proj}\begin{bmatrix}P^{\mathrm{in}}_{\mathrm{CHP},i}\\ P^{\mathrm{in}}_{\mathrm{Boiler},i}\end{bmatrix}=\begin{cases}\begin{bmatrix}P^{\mathrm{in}}_{\mathrm{CHP},i}\\ P^{\mathrm{in}}_{\mathrm{Boiler},i}\end{bmatrix} & \text{if x} \in \text{feasible region}\\ \mathrm{Proj}_{[\mathrm{l,u}]}\left(\begin{bmatrix}P^{\mathrm{in}}_{\mathrm{CHP},i}\\ P^{\mathrm{in}}_{\mathrm{Boiler},i}\end{bmatrix}-\gamma\begin{bmatrix}\eta^{\mathrm{h}}_{\mathrm{CHP},i}\\ \eta_{\mathrm{boiler},i}\end{bmatrix}\right) & \text{otherwise}\end{cases} \quad (C.3)$$

While,

$$\begin{bmatrix}\eta^{\mathrm{h}}_{\mathrm{CHP},i} & \eta_{\mathrm{boiler},i}\end{bmatrix}\mathrm{Proj}_{[\mathrm{l,u}]}\left(\begin{bmatrix}P^{\mathrm{in}}_{\mathrm{CHP},i}\\ P^{\mathrm{in}}_{\mathrm{Boiler},i}\end{bmatrix}-\gamma\begin{bmatrix}\eta^{\mathrm{h}}_{\mathrm{CHP},i}\\ \eta_{\mathrm{boiler},i}\end{bmatrix}\right)=\mathrm{L}_{\mathrm{h},i} \quad (C.4)$$

And,

$$\mathrm{Proj}_{[\mathrm{l,u}]}\begin{bmatrix}P^{\mathrm{in}}_{\mathrm{CHP},i}\\ P^{\mathrm{in}}_{\mathrm{Boiler},i}\end{bmatrix}=\begin{bmatrix}x_1\\ x_2\end{bmatrix} \quad (C.5)$$

$$x_1=\begin{cases}P^{\mathrm{in}}_{\mathrm{CHP},i} & 0\leqslant P^{\mathrm{in}}_{\mathrm{CHP},i}\leqslant \mathrm{Cap}_{\mathrm{CHP},i}\\ 0 & 0>P^{\mathrm{in}}_{\mathrm{CHP},i}\\ \mathrm{Cap}_{\mathrm{CHP},i} & \mathrm{Cap}_{\mathrm{CHP},i}<P^{\mathrm{in}}_{\mathrm{CHP},i}\end{cases} \quad (C.6)$$

$$x_2=\begin{cases}P^{\mathrm{in}}_{\mathrm{Boiler},i} & 0\leqslant P^{\mathrm{in}}_{\mathrm{Boiler},i}\leqslant \mathrm{Cap}_{\mathrm{Boiler},i}\\ 0 & 0>P^{\mathrm{in}}_{\mathrm{Boiler},i}\\ \mathrm{Cap}_{\mathrm{Boiler},i} & \mathrm{Cap}_{\mathrm{Boiler},i}<P^{\mathrm{in}}_{\mathrm{Boiler},i}\end{cases} \quad (C.7)$$

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