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An Integrated Two-Level Demand-Side Management Game Applied to Smart Energy Hubs with Storage

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Abstract

The integration of energy hubs – as an important component of future energy networks that will employ demand-side management techniques – has a key role in the process of efficiency improvement and reliability enhancement of power grids. In such power grids, energy hub operators need to optimally schedule the consumption, conversion, and storage of available resources based on their own utility functions. In sufficiently large networks, scheduling an individual hub can affect the utility of the other energy hubs. In this paper, the interaction between energy hubs is modeled as a *potential game*. Each energy hub operator (player) participates in a dynamic energy pricing market and tries to maximize his own payoff with regard to energy consumption satisfaction. We propose a distributed algorithm based on a potential game, which guarantees the existence of a Nash equilibrium. Furthermore, two different types of signaling are developed and simulation results are compared. Simulation results show that with the implementation of either setup the peak-to-average ratio between electricity networks and natural gas networks diminishes. An analysis of the results shows that either setup can have superiority over the other one with regard to generation costs, convergence rate, price level, and the stability perspective. Hence, energy providers and consumers can choose a favorable setup based on their respective needs.

Keywords: Smart Energy Hub (SEH), Integrated Demand-Response Program, Distributed Demand-Side Management, Storage System

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Nomenclature

$[\dot{\mathbf{E}}]$	Storage flow.
$[\eta]$	Efficiency coefficient matrix of equipment.
$[\mathbf{d}]$	Dispatch factor matrix of different input power.
$[\mathbf{ST}]$	Storage coupling matrix.
α, β, ω	Different types of energy carrier.
κ_i	Proportion of i^{th} user's energy consumption.
$\mathbf{l}^{e/h}$	Electricity/heat demand vectors.
$\mathbf{S}$	Strategy vector.
$\mathcal{F}_i$	Feasible set of strategy vectors for i^{th} user.
$\mathcal{N}$	Set of users (hubs).
$C^{e/g}$	Generation cost of electricity/gas.
$CF_{\alpha\beta}$	Coupling/Conversion factor between input energy carrier α and output energy carrier β.
$m.u.$	Monetary unit
$p.u.$	Per unit
$P_{\alpha,i}$	Input/Output power of i^{th} energy hub.
$pr^{e/g}$	Price of electricity/gas per unit.
t	Time slot.
U	Utility function.
$a_i^{e/h}$	Charge/Discharge rate of electric/heat storage devices of i^{th} energy hub.
$b_i^{e/h}$	Initial energy level of electric/heat storage devices of i^{th} energy hub.
$CAP_i^{e/h}$	Capacity of electric/heat storage devices of i^{th} energy hub.
$D_i^{e/h}$	Energy level of electric/heat storage devices of i^{th} energy hub.

1. Introduction

Modern network-based energy systems, such as electricity, natural gas, and district heating, are mostly designed and operated interdependently [1]. Introducing energy hubs as a leading part of future energy networks provides a great opportunity for energy production, conversion, and storage in such coupled infrastructures for system planners, operators, and prosumers to move towards more energy-efficient and flexible systems [2]. Significant surveys have been carried out on the concept of the energy hub since Giedl et al. [3] introduced it. Many researchers have studied the combined operation of power and natural gas and heat. Mancarella provided a general and critical overview of the latest models and assessment techniques, which are available today for the analysis of multi-energy systems, and particular distributed multi-generation systems DMGS [4].

Propagation of the market penetration level of combined heat and power (CHP) and micro-CHP in multiple countries, along with the utilization of smart grids (SGs) in the electrsicity networks, has paved the way for a smart natural gas infrastructure. As a result, the developing of modern and new methods for Demand Side Management (DSM) in electricity and natural gas networks is crucial. Sheikhi et al. [5] used game theory to model DSM among smart energy hubs (SEHs). Simulation results showed a reduction in both the peak-to-average ratio of the total electricity demand in the Nash equilibrium and the hub users' energy bills. Sheikhi et al. [6] proposed a cloud-computing energy management framework based on integrated demand-side management (IDSM). This IDSM model is based on game theory, which provides an efficient data processing and information management.

For some time scholars have been studying the optimal sizing of components of energy hubs and the optimal scheduling problem of multi-energy hubs. Mohsenian Rad et al. [7] used game theory to formulate an energy consumption scheduling game and showed that optimal scheduling of a single utility company with multiple consumers occurs at Nash equilibrium. Lu et al. [8] designed a transaction mechanism among retailers and consumers in a regional energy market. They demonstrated the existence and the uniqueness of the Nash equilibrium by means of a distributed algorithm with a particle swarm optimization algorithm. Liang et al. [9] proposed a monotonically distributed model and an optimization algorithm for the autonomous energy management of multi-residential energy hubs. Li et al. [2] used a mathematical program with an equilibrium constraint (MPEC) model to identify the strategic behavior of players in an energy hub (EH) in the electricity market and the heating market on two levels. An optimal fair billing mechanism was proposed in [10] that allows increase the fairness level of the system. In the proposed method, customers are charged based on their consumption and rewarded according to their commitment. Huang et al. [11] used a game-theoretic approach for optimal scheduling. They tested it for two case studies; in the first group, they showed that the system cost changes with the total electric load. Results for the second group reveal that the optimal scheduling result of the system is influenced by the variation of the seasons.

In decentralized models, the instantaneous price changes are shared among all the demands and, as a consequence, energy allocation based on their self-determining decision making approaches is triggered by demand signals [12]. ”Integrated demand response” helps multi-energy systems, such as natural gas, district heat/cooling, biomass, and electric power systems, to back up each other in order to constitute a more economical entity. Furthermore, users can exploit their response capability without any loss of energy users' comfort [13]. Most of the studies focus on the optimal operation of energy hubs by considering demand response (DR). Mukherjee et al. [14] analyzed a power-to-gas energy hub in two steps: optimal sizing of the components of the energy hub and the development of a complex optimization model to optimize operation of the hub. Zhang et al. [15] scrutinized the optimal network capacity and the distribution of the CHP-based distributed generation based on urban energy distribution networks by means of an integrated system dispatch model. Tingji et al. [16] proposed a single energy hub for managing battery storage and a PV system with two control strategies for grid-mode and island-mode. Aghamohamadi and Mahmoudi [17] developed an adaptive robust integrated bidding strategy to model energy hubs. Consequently, the energy hubs can bid in multiple energy markets simultaneously in order to optimize their benefits/costs. Bahrami et al. [18] studied the existence and uniqueness of the Nash equilibrium and designed an online distributed algorithm to achieve that equilibrium. They showed that the proposed algorithm can increase the energy hubs' average payoff and the technical performance of the energy network by reducing the peak-to-average ratio (PAR) for both electricity and natural gas. In their paper, game theory was applied to the optimal scheduling of a multi-energy hub system in order improve its economy and robustness. Motalleb and Ghorbani [19] developed a game-theoretical framework where demand response aggregators (DRAs) took part in a competition to sell their stored energy. Noor et al. [20] proposed a game-theoretical approach for a DSM model, incorporating storage components and taking into account the supply constraints in the form of power outages. The proposed model is able to both reduce the PAR and smooth the dips in load profiles caused by supply constraints.

One major concern regarding the simulation of a system of interconnected smart energy hubs which are equipped with storage devices is that of oscillation, which prevents the system from converging properly. In this paper, we have studied the distributed system design of interconnected energy hubs. The main contribution of this paper to the literature can be summarized as follows:

- A distributed integrated demand-side management program is proposed in dynamic pricing markets for electricity and natural gas networks. In the proposed algorithm, each of the SEHs independently bids for its daily profile to the network operator, and other information related to the internal operation of SEHs is kept private.
- Equipping SEHs with storage devices can impose oscillation and prevent the common algorithm from converging properly. We propose a novel modification function in our algorithm which helps the algorithm to converge.
- To coordinate the operation of individual SEHs, two different types of signaling are developed and simulation results are compared. This is significant for those energy companies which provide both electricity and natural gas.
- The proposed method is considerably robust against any probable structural change to the problem. It means that each hub can choose and update its parameters independently and it can apply any strategy without communicating with any of the other hubs.

The remainder of this paper proceeds as follows. In section 2, the SEH concept is presented. Section 3 gives an overview of the decentralized design of the SEH and describes an algorithm which is used in this paper for arranging and modeling the SEH. Furthermore, a load-based setup and a price-based setup are identified in this section. Simulation results are presented in section 4. Conclusions are drawn in section 5.

2. System Model

In this section we introduce the main parts of the model. First, we introduce the concept of demand vectors. Second, the storage model in the smart energy hub is described. Finally, we describe the energy hub model which is equipped with conversion and storage devices.

2.1. Heat and Electricity Demand

Consider $\mathcal{T}$ to be the set of time slots and $\mathcal{N}$ to be the set of consumers, where $T := |\mathcal{T}|$ and $N := |\mathcal{N}|$. We assume that each user has some controllable/shiftable electric loads as well as must-run loads. For each consumer $i \in \mathcal{N}$ the electric energy consumption vector is defined as:

$$\mathbf{l}_i^e = [\, l_i^{e,1}, ..., l_i^{e,t}, ..., l_i^{e,T}], \tag{1}$$

where $l_i^{e,t}$ is the electricity needed by i^{th} consumer to supply his/her appliances at time slot t. To distinguish vectors in the sequel, bold symbols are used. In an analogous way, we can define a heat consumption vector as:

$$\mathbf{l}_i^h = [\, l_i^{h,1}, ..., l_i^{h,t}, ..., l_i^{h,T}], \tag{2}$$

where $l_i^{h,t}$ identifies the amount of heat needed by the i^{th} consumer at time t. Note that we assume a pre-determined daily electricity demand and heat demand vectors $\mathbf{l}_i^e$ and $\mathbf{l}_i^h$, respectively, for each consumer's appliances. Furthermore, a standard load profile has been used which is described in section 4.

2.2. Energy Storage Model

Let a_i^t be the energy charging or discharging rate of the i^{th} consumer's battery at time slot t. For this reason, the energy storage vector for the i^{th} consumer's battery, considering the maximum possible charging and discharging rate in each time slot, is:

$$\mathbf{a}_i^e = [\, a_i^{e,1}, ..., a_i^{e,t}, ..., a_i^{e,T}] \tag{3}$$

$$-a^{e}_{i,max} \leq a^{e,t}_{i} \leq a^{e}_{i,max}, \tag{4}$$

where $a^{e}_{i,max}$ is the maximum electricity charge or discharge rate for one time slot. $a^{e,t}_{i} > 0$ means that the i^{th} consumer is trying to charge their battery and $a^{e,t}_{i} < 0$ means they are trying to discharge it.

The charging and discharging schedule for each battery depends on the schedule in the previous time slots. To prevent overcharging, the battery's stored energy after charging cannot be more than CAP^{e}_{i}, the maximum battery capacity. In order to prevent discharging the battery too much,, the residual stored energy of the battery after discharging must be greater than a specific threshold, which is supposed to be zero. Therefore, the constraint is:

$$0 \leq b^{e,0}_{i} + \sum_{j=1}^{t} a^{e,j}_{i} \leq CAP^{e}_{i}, \quad \forall t \in \mathcal{T}, \tag{5}$$

where b^{0}_{i} stands for the battery's initial charge level. Moreover, we suppose that the desirable charge level, b^{T}_{i}, is known in advance by each consumer. As each consumer has information about the desirable charge level and the initial charge level, the amount of energy required for charging a consumer's battery, D^{e}_{i}, can be obtained as follows:

$$D^{e}_{i} = b^{e,T}_{i} - b^{e,0}_{i}. \tag{6}$$

Accordingly, for charging and discharging the battery, we have the following constraint:

$$\sum_{t=1}^{T} a^{e,t}_{i} = D^{e}_{i}. \tag{7}$$

We can define a similar scheduling vector and constraint for the heat storage devices as follows:

$$\mathbf{a}^{h}_{i} = [\, a^{h,1}_{i}, ..., a^{h,t}_{i}, ..., a^{h,T}_{i}] \tag{8}$$

with the following constraints:

$$-a^{h}_{i,max} \leq a^{h,t}_{i} \leq a^{h}_{i,max} \tag{9}$$

$$0 \leq b_i^{h,0} + \sum_{j=1}^{t} a_i^{h,j} \leq CAP_i^h, \quad \forall t \in \mathcal{T} \tag{10}$$

$$D_i^h = b_i^{h,T} - b_i^{h,0} \tag{11}$$

$$\sum_{t=1}^{T} a_i^{h,t} = D_i^h. \tag{12}$$

2.3. Smart Energy Hub Model

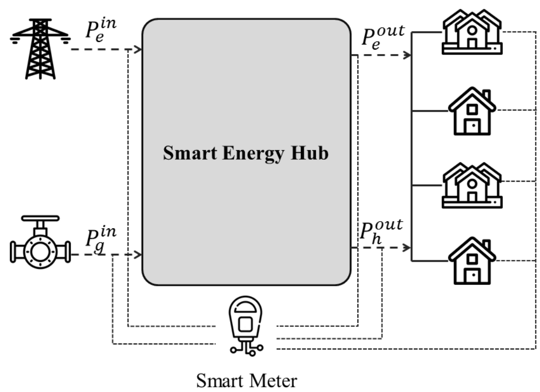

Figure 1: Overall View of a Simple Smart Energy Hub

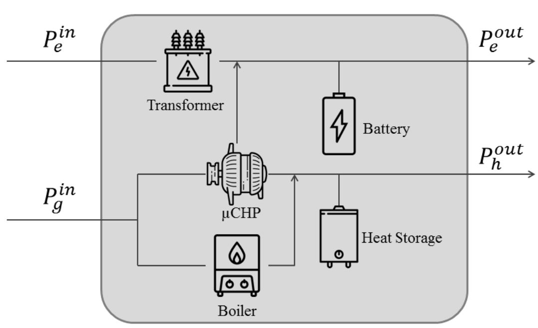

Figure 2: Smart Energy Hub Equipped with Battery and Heat Storage

A smart energy hub is an energy hub which is located in a smart grid that is equipped with smart meters for natural gas and electricity networks and that employs suitable communication infrastructures (Fig. 1). All needed data interchange among the smart meters, using suitable communication protocols such as KNX, ZigBee, or Z-Wave [21]. Power conversion through the hub can be determined from the following equation:

$$\begin{bmatrix} P^{out}_{\alpha,i} \\ P^{out}_{\beta,i} \\ \vdots \\ P^{out}_{\omega,i} \end{bmatrix} = \begin{bmatrix} CF_{\alpha\alpha} & CF_{\beta\alpha} & \dots & CF_{\omega\alpha} \\ CF_{\alpha\beta} & CF_{\beta\beta} & \dots & CF_{\omega\beta} \\ \vdots & \vdots & \ddots & \vdots \\ CF_{\alpha\omega} & CF_{\beta\omega} & \dots & CF_{\omega\omega} \end{bmatrix} \begin{bmatrix} P^{in}_{\alpha,i} \\ P^{in}_{\beta,i} \\ \vdots \\ P^{in}_{\omega,i} \end{bmatrix} \tag{13}$$

where $P^{in}_{\alpha,i}$, $P^{in}_{\beta,i}\dots P^{in}_{\omega,i}$ are the input energy carriers' power corresponding to ith SEH. $P^{out}_{\alpha,i}$, $P^{out}_{\beta,i}, \dots, P^{out}_{\omega,i}$ are the output energy carriers' power and $CF_{\alpha\beta}$ represents the coupling factor between input energy carrier α and the output energy carrier β's energy flow. Equation (13) can be written as:

$$[\mathbf{P}^{out}_i] = [\mathbf{CF}] \times [\mathbf{P}^{in}_i]. \tag{14}$$

Energy hubs may be equipped with energy storage devices on the input side or the output side of converters. In this case, we can mathematically model the energy hub as follows:

$$[\mathbf{P}^{out}_i] = \begin{bmatrix} \mathbf{CF} & -\mathbf{ST} \end{bmatrix} \begin{bmatrix} \mathbf{P}^{in}_i \\ \dot{\mathbf{E}} \end{bmatrix}, \tag{15}$$

where $\mathbf{ST}$ is the coupling storage matrix which indicates the power flow in storage devices. $\dot{E} = E_t - E_{t-1}$ is the vector of the charging/discharging rate in the storage devices. By assuming the efficiency of a converter to be constant, coupling factors could be calculated by multiplying the dispatch factors and the efficiency of the equipment, $[\mathbf{CF}] = [\eta] \times [\mathbf{d}]$. Each element in $[\mathbf{CF}]$ takes a value less than 1.

Therefore, for the sample smart energy hub presented in Fig. 2, the total electric energy demand, $P^{in}_{e,i}$, and total natural gas, $P^{in}_{CHP,i} + P^{in}_{b,i}$, which user i in each time slot, t, purchases from the energy providers to supply that user's appliances and storage devices can be constrained as:

$$l^e = P_e^{out} = \eta_{Tr} P_e^{in} - \frac{a^e}{\eta_e} + \eta_{CHP}^e P_{CHP}^{in} \tag{16}$$

$$l^h = P_h^{out} \leq \eta_{CHP}^h P_{CHP}^{in} + \eta_b P_b^{in} - \frac{a^h}{\eta_h}, \tag{17}$$

where η_{Tr}, η_b, η_{CHP}^e, and η_{CHP}^h are the efficiency of transformer, boiler, electric efficiency of CHP, and heat efficiency of CHP, respectively. We model the charging/discharging losses of the battery and the heat tank as η_e and η_h, respectively, as follows:

$$\eta_{e/h} = \begin{cases} \eta_{e/h}^{+}, & 0 \leq a_{e/h} \\ \frac{1}{\eta_{b/h}^{-}}, & a_{e/h} < 0 \end{cases} \tag{18}$$

Finally, we constrain the operational capacity of the transformer, the CHP, and the boiler with the following equations:

$$0 \leq P_{Tr,i}^{in,t} \leq P_{Tr,i}^{max} \tag{19}$$

$$0 \leq P_{CHP,i}^{in,t} \leq P_{CHP,i}^{max} \tag{20}$$

$$0 \leq P_{b,i}^{in,t} \leq P_{b,i}^{max}. \tag{21}$$

Finally, the feasible energy consumption and storage schedule of the i^{th} consumer can be defined as follows:

$$\mathcal{F}_i = \{\mathbf{P}_i^{in,e}, \mathbf{P}_i^{in,g}, \mathbf{a}_i^e, \mathbf{a}_i^h | \, 4 \; to \; 7 \; - \; 9 \; to \; 12 \; - \; 16 \; to \; 21 \, \}. \tag{22}$$

3. Distributed Configuration

In this section, using a generation cost model, we introduce two different decentralized configurations in which consumers independently maximize their utility by optimizing the energy storage and consump-

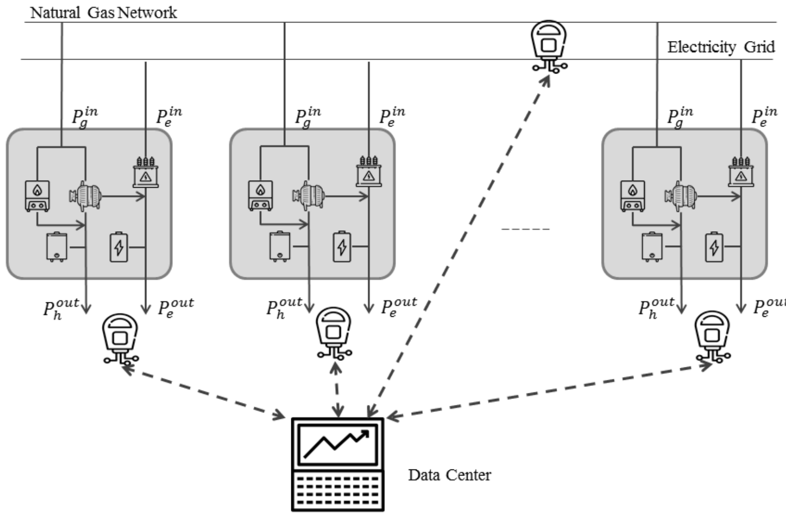

Figure 3: Illustration of Scheduling in Integrated Demand-Side Management

tion strategy vectors based on their individual objective functions. As is shown in Fig. 3, smart energy hubs provide their input from the electricity and gas grids. All SEHs are connected to a data center to which they transfer information based on the model's configuration in the load-based or price-based configuration. This figure displays the energy and information flows in the system. Information flows are represented as a dashed line.

3.1. Generation Cost and Pricing Model

Assume that generating P_t^e units of electric power costs $C^e(P_t^e)$, which is commonly discussed in the literature [22, 23]:

$$C^e(P_t^e) = \delta^e(P_t^e)^2 + \epsilon^e P_t^e, \tag{23}$$

where δ^e and ϵ^e are well-known positive coefficients often used in the smart grid and the energy hub literature. Likewise, we can calculate the total cost of electricity for each time interval as follows:

$$C^e_{total,t} = C^e(\sum_{i=1} P^e_{i,t}). \tag{24}$$

For each time step, the i^{th} consumer would be charged according to the ratio of his consumption to the total demand. Let $\kappa^e_{i,t}$ represent the i^{th} consumer's consumption to the network's load ratio at time slot t:

$$\kappa^e_{i,t} = \frac{P^e_{i,t}}{\sum_{j=1}^{N} P^e_{j,t}}. \tag{25}$$

Finally, in the load-based setup we suppose that the i^{th} consumer would charge proportionally to the total energy demand cost of the system, i.e.

$$C^e_{i,t} = \kappa^e_{i,t} C^e_{total,t}. \tag{26}$$

In Eq. (26), it is obvious that the payment of the i^{th} consumer depends on the total energy cost of the system and that consumer's proportion of the energy demand. For example, if the i^{th} consumer uses twice as much energy as the j^{th} consumer in each time slot t, then consumer i must pay twice as much for energy as consumer j. Analogously, with the same ratiocination, we can derive a natural gas sharing model as follows:

$$C^g(P^g_t) = \delta^g (P^g_t)^2 + \epsilon^g P^g_t. \tag{27}$$

$$C^g_{total} = C^g(\sum_{i=1} P^g_{i,t}). \tag{28}$$

$$\kappa^g_{i,t} = \frac{P^g_{i,t}}{\sum_{j=1}^{N} P^g_{j,t}}. \tag{29}$$

$$C^g_{i,t} = \kappa^g_{i,t} C^g_{total,t}. \tag{30}$$

In the price-based configuration, the utility function depends on the price of energy carriers. The price of each unit of generated energy is simply calculated as follows:

$$Pr^e_{t,p.u} = \frac{C^e_t(P^e_t)}{P^e_t}, \tag{31}$$

where $Pr^e_{t,p.u}$ is the price of each unit of electric energy generated. With the same ratiocination, we can formulate a natural gas cost model as follows:

$$Pr^g_{t,p.u} = \frac{C^g_t(P^g_t)}{P^g_t}. \tag{32}$$

3.2. Setup I: Load-Based Setup

In this setup, aggregated load profiles of the networks are shared between users in each iteration, and users update their strategy vectors based on this information. Here, users can calculate the price of different energy carriers and maximize their utility (minimize their payment).

For each user $i \in \mathcal{N}$, the utility function can be seen as the negative energy payment over T time slots. As total demand affects the energy price, the energy payment that each user pays to the energy provider depends on both their own energy demand and also on the other users' energy demands. Eq. (33) represents the strategy vector of user $i \in \mathcal{N}$:

$$\mathbf{S}_i = [\mathbf{P}^e_i, \mathbf{P}^g_i, \mathbf{a}^e_i, \mathbf{a}^h_i]. \tag{33}$$

Following this, by plugging Eq. (26) and Eq. (30) into Eq. (33), the final utility function can be derived as follows:

$$\begin{aligned} &U_i(\mathbf{S}_i, \mathbf{S}_{-i}) = -C_i = \\ &-\sum_{t=1}^{T}[\,\kappa^e_{i,t}(\delta^e(P^e_{i,t} + P^e_{-i,t})^2 + \epsilon^e(P^e_{i,t} + P^e_{-i,t})) \\ &+\kappa^g_{i,t}(\delta^g(P^g_{i,t} + P^g_{-i,t})^2 + \epsilon^g(P^g_{i,t} + P^g_{-i,t}))], \end{aligned} \tag{34}$$

where $P^e_{-i,t}$ and $P^g_{-i,t}$ denote the sum of electricity and natural gas demand, of all users except user i at time slot t, respectively. Simply, $P_{-i} = \sum_j P_j | j \neq i$. $\mathbf{S}_i$ consists of the load profile vectors of energy consumption of user i. $\mathbf{S}_{-i} := [\,\mathbf{S}_1, \mathbf{S}_2, \ldots \mathbf{S}_{i-1}, \mathbf{S}_{i+1} \ldots, \mathbf{S}_N]$ denotes the vectors of the electricity and natural gas load profiles that all users except user i choose. As a side note, in the utility function (Eq. 34), the cost of battery lifetime reduction is neglected.

3.3. Setup II: Price-Based Setup

Energy prices are significant incentive signals for users to consume different kinds of energy carriers rationally. Therefore, the design of a pricing mechanism can considerably influence the scheduling strategies of users in an energy hub. In this setup, an independent system operator receives the electricity and natural gas demand of all users and calculates the price of each carrier for each time slot based on the following equations. Users will be informed about the price profiles of different energy carriers in each iteration and will update their strategies. Consequently, they can maximize their utility according to the price profile of different energy carriers.

The utility function of each user $i \in \mathcal{N}$, over total time slots can be identified as a negative payment. The energy bill of each user simply depends on the energy unit price – which is calculated by the independent system operator (ISO) – and the user's own energy demand. Using Eqs. (31) and (32), we can rewrite Eq. (34) for this configuration as follows:

$$\begin{aligned} U_i(\mathbf{S}_i, \mathbf{S}_{-i}) &= -C_i \\ &= -\sum_{t=1}^{T}[Pr^{e}_{t,p.u} \times P^{e}_{i,t} + Pr^{g}_{t,p.u} \times P^{g}_{i,t}]. \end{aligned} \tag{35}$$

3.4. Game-Theoretical Model

In a distributed smart energy hub system, each consumer $i \in \mathcal{N}$, independently of the others, tries to minimize his/her energy costs, which leads to a non-cooperative energy consumption and storage (NCECS) game among end-users. This game is defined by three components:

$$G = \{\mathcal{N}, \{\mathcal{F}_i\}_{i\in\mathcal{N}}, \{U_i\}_{i\in\mathcal{N}}\} \tag{36}$$

- The players, who are the consumers in the set $\mathcal{N}$;
- The strategy of each consumer $i \in \mathcal{N}$, which corresponds to the energy consumption and storage vectors, $\mathbf{S}_i \in \mathcal{F}_i$; and
- The utility function U_i of each consumer $i \in \mathcal{N}$ as in Eq. (34) or (35).

Based on the definition of the utility and strategies in the NCECS game, in order to maximize the utility function, each consumer tries to select his energy consumption, conversion, and battery charging/discharging schedules. The best response strategy is when the i^{th} player (consumer) aims at maximizing his utility function, while assuming that all other consumers' strategies are fixed. For each consumer $i \in \mathcal{N}$, the best response strategy is:

$$\mathbf{S}_i^{best} \in \mathrm{argmax}_{\mathbf{S}_i \in \mathcal{F}_i} U_i. \tag{37}$$

Thus, for any consumer, any best response strategy, $\mathbf{S}_i^*$, is as least as good as every other strategy in $\mathcal{F}_i$ when the strategies of the other users, $\mathbf{S}_{-i}$, are fixed. For the defined NCECS game, the Nash equilibrium is defined as follows.

Definition: Consider the NCECS game, with utility function U_i given by Eq. (34) or (35). A vector of strategies $\mathbf{S}^*$, if and only if it satisfies the following set of inequalities, constitutes a Nash equilibrium of the NCECS game.

$$U_i(\mathbf{S}_i^*, \mathbf{S}_{-i}^*) \geq U_i(\mathbf{S}_i, \mathbf{S}_{-i}^*) \quad \forall (\mathbf{S}_i) \in \mathcal{F}_i, \forall i \in \mathcal{N}. \tag{38}$$

A *Nash equilibrium* of the NCECS game represents a status in which no user can increase his/her utility by changing the energy consumption and storage schedules while the strategy of all other consumers are fixed. Now, we can propose the NCECS game algorithm as shown in Table 1. This is an iterative-based solution which is applied by the system operator. In the first step, some coefficient and variables are initialized. In each iteration, the system operator announces the modified aggregated load/price profile of the energy carriers to each agent (hub). Each agent optimizes his strategy vector based on the announce load/price profiles and announces his demand profile and the value of the objective function. Again, the system operator calculates the modified aggregated load/price profiles and announces it to the agents. This procedure is repeated until the value of the objective function of all agents in two consecutive iteration differs less than the defined value (Δ).

Table 1: Algorithm of the Proposed Method

1. Initialization: $j = 1$, $\Delta = 10^{-2}$, cost coefficients and $S_i = 0$
2. Repeat algorithm
3. Receive modified aggregated P^e_{in} and P^g_{in} or the price profile of the carriers
4. For each hub (parallel)
5. Update strategy vector S^k_i according to P^e_{in} and P^g_{in} using S^0_i
6. Update input powers according to S_i
7. End
8. S^0_i=S^k_i
9. $j = j + 1$
Until: for all users $\|U^{j+1}_i - U^j_i\| \leq \Delta$

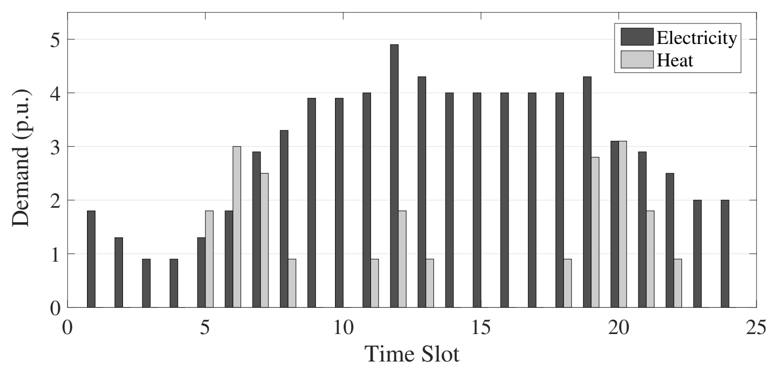

Figure 4: Electricity and Heat Demand for a Sample Energy Hub (Per Unit)

4. Performance Evaluation

Five hubs are considered in this study which are connected to electricity and natural gas networks (Fig. 3) and one electricity company and one natural gas company each exist in the proposed energy system. $T = 24$ time slots have been considered. The electrical and heat load demands for a sample energy hub are considered for a sunny summer day in Germany (Fig. 4) and each considered hub follows this pattern with a coefficient as presented in Table 2. For all hubs, the efficiency coefficient of the equipment is mentioned in Table 3. Furthermore, for the sake of simplicity, heat demand is assumed to be satisfied instantly in the hubs.

The optimization problem for each hub includes 24 equality constraints and 456 inequality constraints. They have 168 decision variables. All simulations were performed in MATLAB-R2015b, run-

Table 2: Demand Coefficients and Storage Capacity of Different Hubs.

	Hub 1	Hub 2	Hub 3	Hub 4	Hub 5
L_e Coefficient	1	0.8	1.2	0.8	1.2
L_h Coefficient	1	0.8	1.2	0.8	1.2
Heat Storage Capacity (p.u)	4	✗	3	3.5	4.5
Battery Capacity (p.u)	5	6	✗	4.5	4

Table 3: Simulation Constants

$\eta_{t,i}$	$\eta_{e,chp}$	$\eta_{h,chp}$	η_{boiler}
0.99	0.3	0.4	0.75

ning in Windows 10 64-bit, using a personal computer equipped with an Intel Core i7 processor. The proposed algorithm is run for different numbers of SEHs. Fig. 5 illustrates that the running time increases slightly with number of SEHs. Hence, it can concluded that the proposed method can also be used for a system with a large number of SEHs.

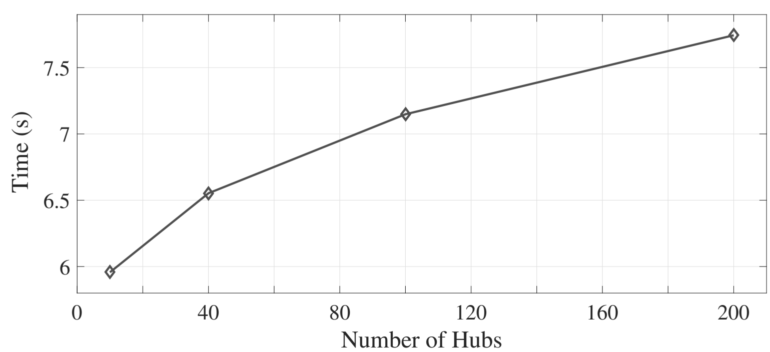

Figure 5: Average Required Time to Reach Proper Convergence

4.1. General System Operation

Fig. 6 shows the total electricity input power in the presence and absence of two configurations of the smart energy hubs. In both the load-based and the price-based scheme, aggregated electric power input into the hubs, which is equal to the electrical power generated by the suppliers, is not only reduced during peak hours but is also increased in off-peak hours. It means that the consumers buy electricity during the

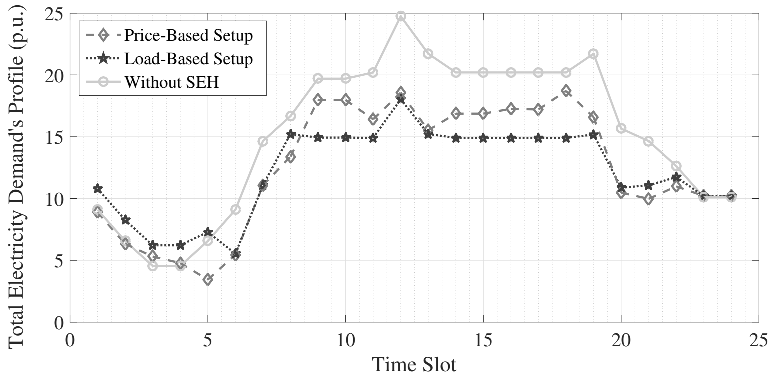

Figure 6: Sum of Electrical Input Power (Per Unit) for the Two Setups and without SEH

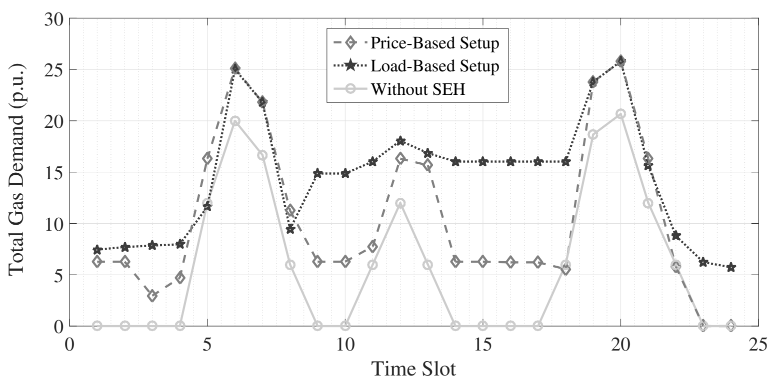

Figure 7: Sum of Natural Gas Input Power (Per Unit) for the Two Setups and without SEH

off-peak periods, store it in their battery, and use it during the peak periods of a day. Fig. 7 shows the total natural gas input power into the hubs, which is equal to the natural gas that the utility company sells in the aforementioned scheme. Aggregate gas input power is flattened by using SEH. Thus, end-users prefer to buy more natural gas during electricity network peaks and to convert it into electricity, as this is cheaper than buying electricity from the grid.

Fig. 6 indicates that the peak demand profile of electricity for load-based and price-based setups is reduced by 27.1% and 24.4%, respectively. As Fig. 7 shows, the peak of the demand profile of the natural gas network for both load-based and price-based setups is increased by 24.8%.

The PAR index is used to quantify imbalance in the daily energy consumption's load base. As is

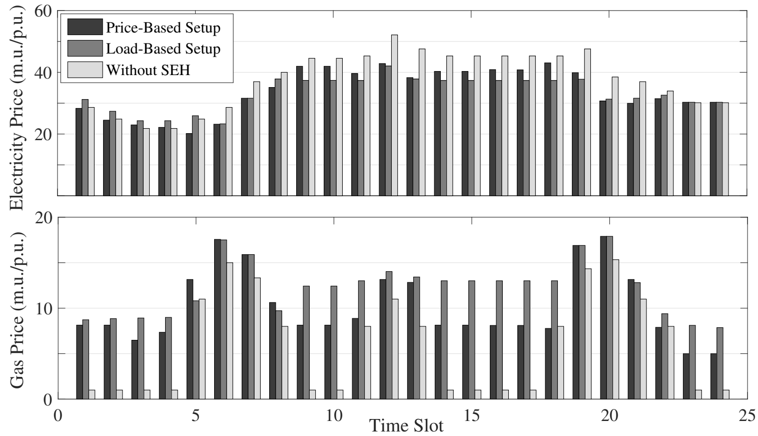

Figure 8: Price Profile of Energy carriers in Different Setups

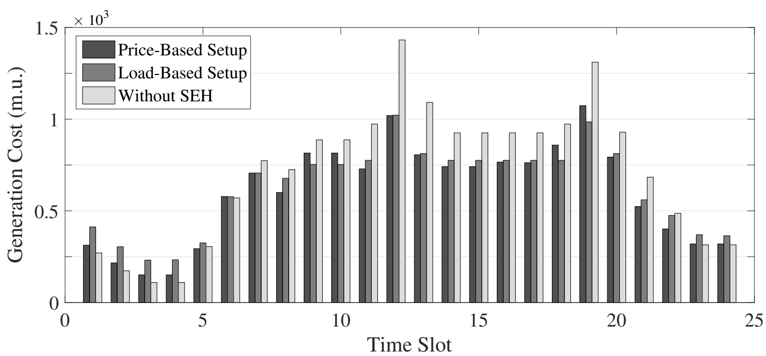

Figure 9: Total Generation Cost in Different Setups

shown in Eq. (39); the PAR is the ratio of the average energy consumption in peak time to the energy consumption during one day.

$$PAR = \frac{max P_{\alpha}^{in}(t)}{\sum\limits_{t=1,2,\ldots 24} P_{\alpha}^{in}(t)/24}. \tag{39}$$

The PAR for electricity without SEH is 1.64 and with SEH for the load-based setup and the price-based setup is 1.48 and 1.49, respectively, which reflects a 9.3% decrease in the aggregate load demand for electricity in the load-based setup and a 8.5% decrease in the price-based setup.

The PAR for natural gas without SEH is 3.49 and with SEH for the load-based setup and the price-based setup it is 1.79 and 2.48, respectively, which reflects a 48.7% decrease in the aggregate load demand for natural gas in the load-based setup and a 28.9% decrease in the price-based setup. It implies that applying both configurations of the SEH will be appropriate for the natural gas network.

As is shown in Figs. 6 and 7, the price-based setup results in more fluctuation in the aggregated load profile than the load-based setup does, which can induce more instability in energy networks. Fig. 8 demonstrates the energy price profiles for different configurations. As is show in this figure, on the one hand, the prices in the electricity network decrease during peak times of the day due to the reduction in electricity consumption. On the other hand, gas prices during the day increase due to the increase in consumption. However, simulation results show a reduction in the energy bills in both configurations. As an illustration, at the end of the simulated day, user 1 has to pay 3.6×10^3 units of money ($m.u.$) to energy providers without the implementation of smart energy hubs while these payments reduce to $2.92 \times 10^3 m.u.$ and $2.80 \times 10^3 m.u.$ for the load-based setup and the price-based setup, respectively.

Fig. 9 represents the total energy generation cost for conventional systems (without SEH) and the two proposed setups at different times of the day. As is shown in this figure, the generation cost for the conventional system is much higher than for the other setups at most of the time during the day. For instance, the generation cost without implementing SEH at 12:00 and 13:00 hrs is at least 28.2% and 25.1% higher than the other setups. The total generation cost for the day without implementing SEH is $1.68 \times 10^4 m.u.$, for the load-based setup it is $1.48 \times 10^4 m.u.$ and for the price-based setup it is $1.42 \times 10^4 m.u.$, which shown an 11.9% and a 15.5% reduction, respectively.

4.2. The Load-Based Setup

Fig. 10 presents the convergence process of total electricity and natural gas demand for 5 different sample time slots by implementing the load-based setup. Fig 11 shows the convergence process in CHPs and Boilers of different hubs for an example time slot using the load-based setup. As is shown in this figure, this setup needs 14 iterations to reach an acceptable convergence.

Fig. 12 represents the level of electrical power stored in the batteries for the load-based load base setup. Since the third hub does not have a battery and only has heat storage, it is not shown in Fig. 12. As is shown in this figure, during the off-peak period of the day between 12:00 to 06:00 hrs, the batteries gradually begin to charge and during the peak hours they discharge. During the final hours of the day the

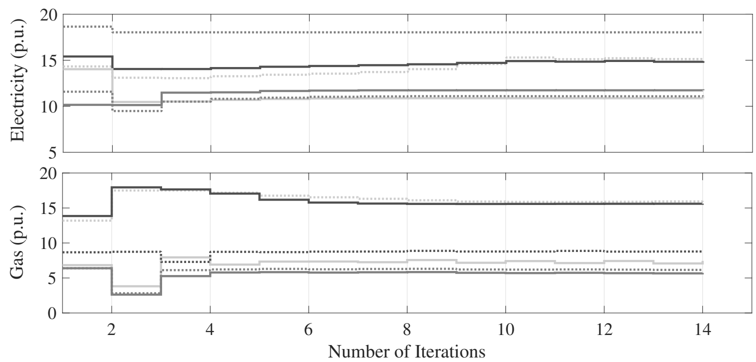

Figure 10: Convergence of Electricity and Gas Demand in Load-Based Setup for 5 Energy Hubs in Sample Time Slots

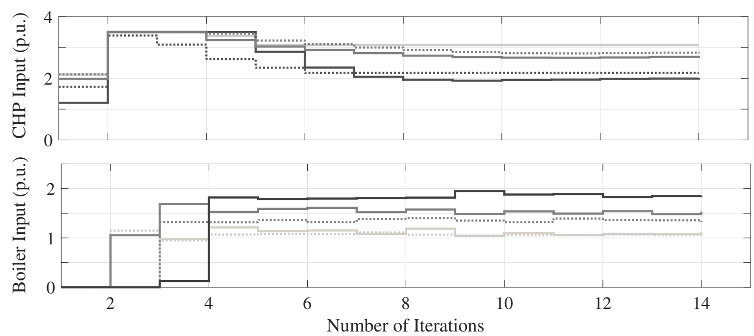

Figure 11: Convergence of CHP and Boiler's Input in Load-Based Setup for 5 Energy Hubs in Sample Time Slots

storage level of the batteries reduces to the minimum allowed level. Fig. 13 represents the level of heat power stored in the heat tanks for this setup. As the second hub includes only an electrical storage device, it is not shown in this figure. As is shown in this figure, similarly to Fig. 12, the level of stored energy in the heat tank increases and reaches its maximum level before the peak hours of the day.

4.3. The Price-Based Setup

Fig. 14 shows the convergence process of the price of electricity and the price of natural gas for 6 different example time slots by implementing the price-based setup. As is shown in this figure, after 24 iterations the acceptable convergence is obtained.

Figs. 15 and 16 represent the level of electrical power and heat power stored in storage devices in different hubs for the proposed price-based setup. Similarly to the load-based setup, in the price-based

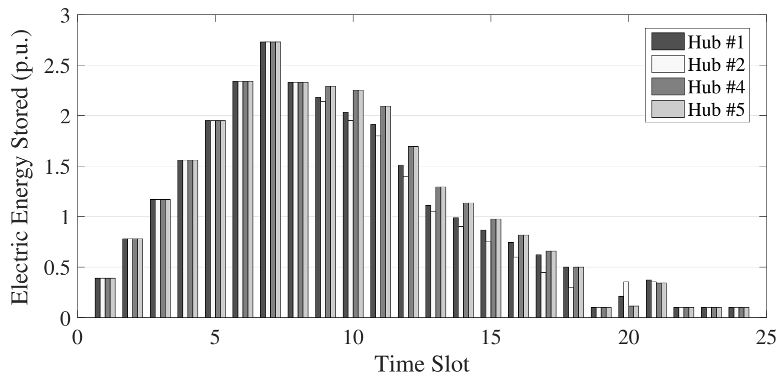

Figure 12: Electrical Energy Stored in Different Hubs in the Load-Based Setup

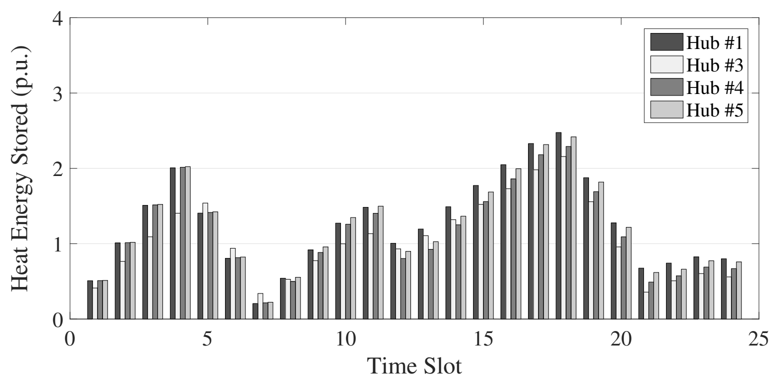

Figure 13: Heat Energy Stored in Different Hubs in the Load-Based Setup

setup both electrical and heat storage devices charge during off-peak hours and they discharge during the peak period but with different patterns. It can be seen that, similarly to the load-based setup, users with must-run loads can participate in this program and use storage devices for shifting their demand to the off-peak hours of a day.

5. Conclusion

In this paper, a novel robust distributed algorithm has been proposed for modeling a system of interconnected smart energy hubs. The paper also describes how users can participate in integrated demand-side management (IDMG). A non-cooperative congestion game model was used in which users independently optimize their energy consumption and storage schedule. To evaluate the performance of the

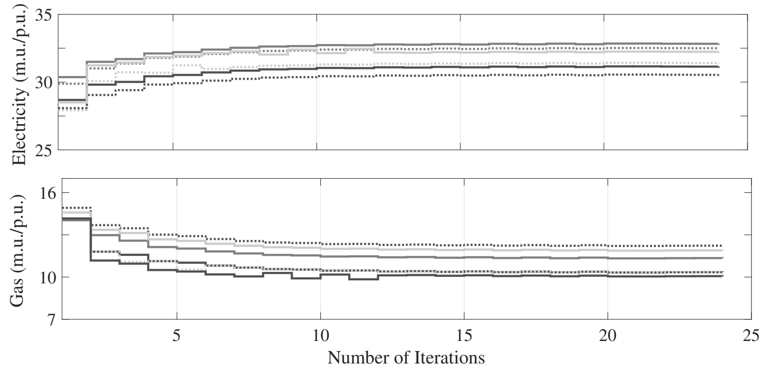

Figure 14: Convergence of Electricity and Gas Prices in Price Based Setup for 5 Energy Hubs in Sample Time Slots

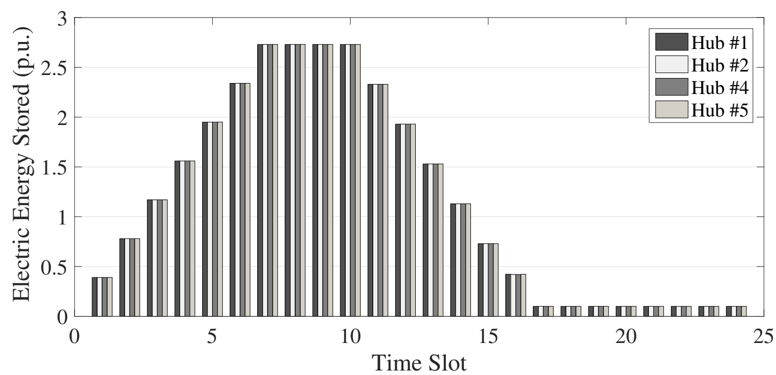

Figure 15: Electrical Energy Stored in Different Hubs when Implementing the Price-Based Setup

proposed algorithm, a benchmark with five hubs equipped with storage devices, including battery and heat tank, was investigated. Since this model does not converge properly due to non-convexity of the problem, an estimation function was used to decrease the gap between the maximum and minimum of the aggregated load profile. In this model, users can take part in the program both by shifting their load demand (using storage devices) or by switching their energy sources. Moreover, connecting storage devices to an SEH leads to a considerable reduction of the peak-to-average ratio for both electricity and natural gas networks. In order to verify the effectiveness of the proposed algorithm, two different signaling schemes (i.e. the price-based and the load-based setups) have been compared. Simulation results show a 27.1% and 24.4% reduction of the peak load only in electricity networks for the load-based and price-based setup, respectively. Furthermore, the daily energy bill is reduced by 11.9% and 15.5% in the

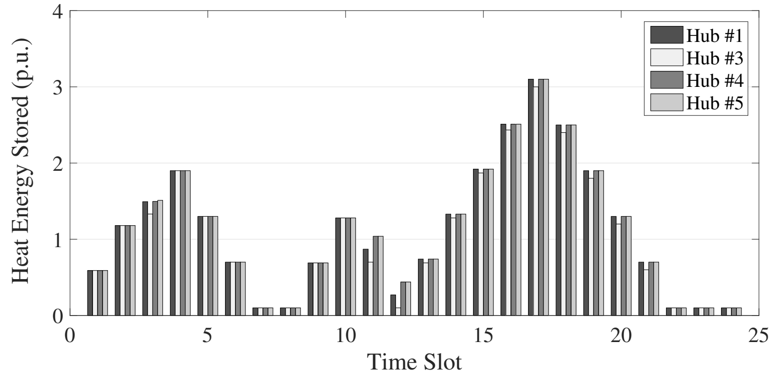

Figure 16: Heat Energy Stored in Different Hubs when Implementing of the Price-Based Setup

load-based setup and price-based setup, respectively. However, the price-based setup shows more instability because of price fluctuations. Comparing convergence rate of the two setups demonstrates that the load-based setup converges faster. In summary, this paper provides a useful instrument for energy utility companies to choose an appropriate configuration based on their operational constraints and policies. In future studies, the proposed algorithm can be simulated on a real system of smart energy hubs with a noticeable share of renewable in order to evaluate its performance. When doing so, grid parameters, such as the power transmission capacity of lines, can also be taken into account. Furthermore, the optimal signaling mechanism design for a network of interconnected energy hubs could be scrutinized.

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References

[1] M. Arnold, G. Andersson, Decomposed electricity and natural gas optimal power flow, in: 16th Power Systems Computation Conference (PSCC 08), Glasgow, Scotland, Citeseer, 2008 (2008).

[2] R. Li, W. Wei, S. Mei, Q. Hu, Q. Wu, Participation of an energy hub in electricity and heat distribution markets: An MPEC approach, IEEE Transactions on Smart Grid (2018).

[3] M. Geidl, G. Koeppel, P. Favre-Perrod, B. Klöckl, G. Andersson, K. Fröhlich, The energy hub–A powerful concept for future energy systems, in: Third annual Carnegie Mellon Conference on the Electricity Industry, Pittsburgh, 2007, pp. 13–14 (2007).

[4] P. Mancarella, MES (multi-energy systems): An overview of concepts and evaluation models, Energy 65 (2014) 1–17 (2014).

[5] A. Sheikhi, S. Bahrami, A. M. Ranjbar, An autonomous demand response program for electricity and natural gas networks in smart energy hubs, Energy 89 (2015) 490–499 (2015).

[6] A. Sheikhi, M. Rayati, S. Bahrami, A. M. Ranjbar, Integrated demand side management game in smart energy hubs, IEEE Transactions on Smart Grid 6 (2) (2015) 675–683 (2015).

[7] A.-H. Mohsenian-Rad, V. W. Wong, J. Jatskevich, R. Schober, A. Leon-Garcia, Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid, Smart Grid, IEEE Transactions on 1 (3) (2010) 320–331 (2010).

[8] Q. Lu, S. Lü, Y. Leng, A Nash-Stackelberg game approach in regional energy market considering users' integrated demand response, Energy 175 (2019) 456–470 (2019).

[9] Y. Liang, W. Wei, C. Wang, A generalized Nash equilibrium approach for autonomous energy management of residential energy hubs, IEEE Transactions on Industrial Informatics (2019) 1–1 (2019).

[10] T. Assaf, A. H. Osman, M. Hassan, Fair autonomous energy consumption scheduling based on game-theoretic approach for the future smart grid, in: Computer Modelling and Simulation (UKSim), 2016 UKSim-AMSS 18th International Conference on, IEEE, 2016, pp. 235–239 (2016).

[11] Y. Huang, W. Zhang, K. Yang, W. Hou, Y. Huang, An optimal scheduling method for multi-energy hub systems using game theory, Energies 12 (12) (2019) 2270 (2019).

[12] A. R. Vahabi, M. A. Latify, M. Rahimiyan, G. R. Yousefi, An equitable and efficient energy management approach for a cluster of interconnected price responsive demands, Applied Energy 219 (2018) 276–289 (2018).

[13] J. Wang, H. Zhong, Z. Ma, Q. Xia, C. Kang, Review and prospect of integrated demand response in the multi-energy system, Applied Energy 202 (2017) 772–782 (2017).

[14] U. Mukherjee, S. Walker, A. Maroufmashat, M. Fowler, A. Elkamel, Power-to-gas to meet transportation demand while providing ancillary services to the electrical grid, in: Smart Energy Grid Engineering (SEGE), IEEE, 2016, pp. 221–225 (2016).

[15] X. Zhang, G. G. Karady, S. T. Ariaratnam, Optimal allocation of chp-based distributed generation on urban energy distribution networks, IEEE Transactions on Sustainable Energy 5 (1) (2014) 246–253 (2014).

[16] C. Tingji, T. Anping, W. Yuhuai, L. Guojie, X. Jing, A multiport energy hub for the connection of multi power flow: A simulating case, in: 2017 IEEE Conference on Energy Internet and Energy System Integration (EI2), IEEE, 2017, pp. 1–5 (2017).

[17] M. Aghamohamadi, A. Mahmoudi, From bidding strategy in smart grid toward integrated bidding strategy in smart multi-energy systems, an adaptive robust solution approach, Energy (2019).

[18] S. Bahrami, M. Toulabi, S. Ranjbar, M. Moeini-Aghtaie, A. M. Ranjbar, A decentralized energy management framework for energy hubs in dynamic pricing markets, IEEE Transactions on Smart Grid 9 (6) (2018) 6780–6792 (2018).

[19] M. Motalleb, R. Ghorbani, Non-cooperative game-theoretic model of demand response aggregator competition for selling stored energy in storage devices, Applied Energy 202 (2017) 581–596 (2017).

[20] S. Noor, W. Yang, M. Guo, K. H. van Dam, X. Wang, Energy demand side management within micro-grid networks enhanced by blockchain, Applied Energy 228 (2018) 1385–1398 (2018).

[21] Á. San-Salvador, Á. Herrero, Contacting the devices: a review of communication protocols, in: Ambient Intelligence-Software and Applications, Springer, 2012, pp. 3–10 (2012).

[22] C. Wu, H. Mohsenian-Rad, J. Huang, A. Y. Wang, Demand side management for wind power integration in microgrid using dynamic potential game theory, in: GLOBECOM Workshops (GC Workshops), IEEE, 2011, pp. 1199–1204 (2011).

[23] A. J. Wood, B. F. Wollenberg, Power generation, operation, and control, John Wiley & Sons, 2012 (2012).

[24] S. O. Sobhani, S. Sheykhha, M. R. Azimi, R. Madlener, Two-level distributed demand-side management using the smart energy hub concept, Energy Procedia 158 (2019) 3052–3063 (2019).

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