PAPER

Blockchain-Based Optimization of Distributed Energy Management Systems with Real-Time Demand Response

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SUMMARY Design of distributed energy management systems composed of several agents such as factories and buildings is important for realizing smart cities. In addition, demand response for saving the power consumption is also important. In this paper, we propose a design method of distributed energy management systems with real-time demand response, in which both electrical energy and thermal energy are considered. Here, we use ADMM (Alternating Direction Method of Multipliers), which is well known as one of the powerful methods in distributed optimization. In the proposed method, demand response is performed in real-time, based on the difference between the planned demand and the actual value. Furthermore, utilizing a blockchain is also discussed. The effectiveness of the proposed method is presented by a numerical example. The importance of introducing a blockchain is pointed out by presenting the adverse effect of tampering the actual value.

key words: *ADMM, blockchain, demand response, distributed energy management systems, distributed optimization*

1. Introduction

Control technologies for realizing a smart city have attracted much attention (see, e.g., [4]). In a smart city, it is important to apply several technologies to many services such as transportation, energy distribution, healthcare, environmental monitoring, business, commerce, emergency response, and social activities. In this paper, we focus on design of distributed energy management systems (EMSs). A distributed EMS is composed of several agents such as factories and buildings (see, e.g., [17]–[20]). By transactions between agents, the surplus power may be generated. As a result, the power traded with an external district can be controlled. In the existing methods, day-ahead scheduling has been mainly studied.

In EMSs, demand response (DR) is one of the key technologies. DR is defined as the changes in electricity usage of end-use consumers by changing the electricity price, the incentive, and so on (see, e.g., [1]). There have been many results from several viewpoints such as distributed DR and model predictive control (see, e.g, [7], [12], [16], [21], [25]). In [7], [21], the future demand is re-scheduled based on the error of the past planned demand and the past actual power consumption, based on the policy of model predictive control. We suppose that the amount of modification of the future demand is compensated by DR. Such DR is called here a real-time DR [7]. In these methods, a distributed EMS composed of multiple agents has not been considered. For a distributed EMS, it is important to develop an optimization method for re-scheduling considering DR. However, only few results have been obtained so far (see, e.g, [2], [11], [26]).

On the other hand, it is important to prevent tampering with the data set stored in computers. There are several purposes in tampering by attackers. When a large-scale plant composed of factories and buildings is modeled by a distributed EMS, one of the typical purposes of attackers is that economic damage is caused. In [7], [21], whether DR is performed or not is decided based on the past/current actual consumption and the planned demand. Then, there is a possibility that inappropriate DR is performed by tampering with the past/current actual consumption and the planned demand. Such tampering can be prevented by using a blockchain. A blockchain is a distributed ledger, and has been widely used (see, e.g., [5], [10]). For EMSs, several results have been obtained (see, e.g., [13], [22], [23]). For also DR, several results have been obtained (see, e.g., [14], [24]). However, to the best of our knowledge, applications of a blockchain to a distributed EMS with DR have not been studied.

In this paper, based on the problem setting of [17]–[20], [23], we propose a new method for day-ahead scheduling and re-scheduling for a distributed EMS considering both electrical energy and thermal energy. The error between the past planned demand and the past actual value is distributed to the demands at certain future times. In both day-ahead scheduling and re-scheduling, we use ADMM (Alternating Direction Method of Multipliers), which is one of the powerful methods in distributed optimization [3]. ADMM is frequently used in power systems (see, e.g., [6], [9], [18]). A numerical example is presented to show the effectiveness of the proposed method. By this numerical example, we also discuss the adverse effect of tampering and the computation time.

This paper is organized as follows. In Sect. 2, the exchange problem and ADMM are summarized as preliminaries. In Sect. 3, a distributed EMS studied in this paper is explained. In Sect. 4, the proposed optimization method is explained. In Sect. 5, a numerical example is presented. In Sect. 6, we conclude this paper.

Notation: Let $\mathcal{R}$ denote the set of real numbers. For the finite set $\mathcal{A}$, let $|\mathcal{A}|$ denote the number of elements in $\mathcal{A}$. Let $0_{m\times n}$ denote the $m \times n$ zero matrix. For the vector x, let $x^\top$ denote the transpose of x. For the vector x, let $\|x\|_2$

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denote the Euclidean norm of x. For the vector x, let $x^{(i)}$ denote the i-th element of x.

2. Exchange Problem and ADMM

In this section, first, the exchange problem (EP) is explained. Next, ADMM is explained as one of the solution methods for EP.

Let $\mathcal{I} = \{1, 2, \ldots, n\}$ denote the set of agents. Let x_i, $\mathcal{X}_i$, and $f_i : \mathcal{X}_i \to \mathcal{R}$ denote the decision variable vector, the domain of x_i, and the convex objective function, respectively. Let $\mathcal{M}$ denote the finite set of markets. Let $x_i^{(m_j)}$, $j \in \{1, 2, \ldots, |\mathcal{M}|\}$ denote the scalar decision variable for the agent i in the market $m_j \in \mathcal{M}$ (note that $x_i^{(m_j)}$ is the m_j-th element of the vector x_i). The vector $x_i^{\mathcal{M}}$ is defined by $x_i^{\mathcal{M}} := [x_i^{(m_1)}\ x_i^{(m_2)}\ \cdots\ x_i^{(m_{|\mathcal{M}|})}]^\top$. Using a certain matrix M_i, the relation between x_i and $x_i^{\mathcal{M}}$ is given by $x_i^{\mathcal{M}} = M_i x_i$. Then, EP is given as follows:

$$\begin{aligned} \text{(EP)} \quad & \text{find} \quad x_i,\ i \in \mathcal{I} \\ & \text{minimize} \quad \sum_{i \in \mathcal{I}} f_i(x_i) \\ & \text{subject to} \quad x_i \in \mathcal{X}_i,\ i \in \mathcal{I}, \\ & \qquad \sum_{i \in \mathcal{I}} x_i^{\mathcal{M}} = 0_{|\mathcal{M}| \times 1}. \end{aligned} \tag{1}$$

In EP, a sum of objective functions for agents is minimized under the condition that demand and supply are balanced in all markets. For the market $m \in \mathcal{M}$, the agent i is called a supplier if $x_i^{(m)} < 0$, and the agent i is called a consumer if $x_i^{(m)} > 0$.

Next, the Lagrange function for EP is given by

$$L(x_1, x_2, \ldots, x_n, \alpha) = \sum_i f_i(x_i) + \alpha^\top \sum_i x_i^{\mathcal{M}},$$

where $\alpha \in \mathcal{R}^{|\mathcal{M}|}$ is a Lagrange multiplier, and corresponds to a shadow price in the market. For each agent, this Lagrange function can be decomposed to

$$L_i(x_i, \alpha) = f_i(x_i) + \alpha^\top x_i^{\mathcal{M}},\ i \in \mathcal{I}.$$

In the case of using ADMM for EP, x_i and α are updated as follows:

$$\begin{aligned} x_i(k+1) &= \mathop{\arg\min}_{x_i \in \mathcal{X}_i} \Big(L_i(x_i, \alpha(k)) + \frac{\rho}{2} \| x_i^{\mathcal{M}} - x_i^{\mathcal{M}}(k) \\ &\qquad + \bar{x}^{\mathcal{M}}(k) \|_2^2 \Big),\ i \in \mathcal{I}, \end{aligned} \tag{2}$$

$$\alpha(k+1) = \alpha(k) + \rho \bar{x}^{\mathcal{M}}(k+1), \tag{3}$$

where $k \in \{0, 1, 2, \ldots\}$ is the number of updates (turn), ρ is a penalty parameter given as a constant, and $\bar{x}^{\mathcal{M}}(k) = \sum_i x_i^{\mathcal{M}}(k)/n$. Using (2) and (3), we can obtain the optimal solution to EP. See [18] for further details on the convergence to the optimal solution.

In distributed optimization using ADMM, the whole system consists of an aggregator and n agents (see also Fig. 1). The aggregator presents the shadow price α and the mean value $\bar{x}$ to each agent, and collects $x_i^{\mathcal{M}}(k+1)$ obtained by local optimization in each agent. In addition, α is updated using $\bar{x}^{\mathcal{M}}(k+1)$. In each agent, the individual local optimization problem is solved.

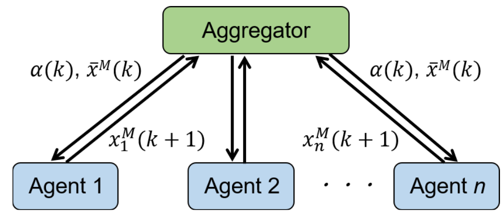

Fig. 1 Distributed optimization using ADMM.

3. Distributed Energy Management Systems

In this section, we formulate a distributed EMS. A mathematical model of a distributed EMS in this paper is based on [17]–[20].

Consider a special district that is composed of factory agents and building agents. These agents are independent. Each agent has thermal and electrical demand given in advance. In this section, we consider only a single period. A factory agent has energy conversion equipments such as boilers and turbines, and can sell surplus energy to other agents. In a building agent, to satisfy its demand, energy from inside and outside of the district is purchased, and energy conversion equipments are operated. Here, there are two markets, i.e., an electricity market and a heat market.

First, we explain a factory agent (see also Fig. 2). Suppose that a factory agent has a gas cogeneration system (GT) and a gas boiler (BA). The optimization problem for a factory agent is given as follows:

$$\text{minimize} \quad \alpha_{BE} BE + \alpha_{BG} BG + \alpha_{\mathrm{E}} SE_{\mathrm{E}} + \alpha_{\mathrm{H}} SH_{\mathrm{H}} \tag{4}$$

$$\begin{aligned} \text{subject to} \quad & SE_{\mathrm{E}} \le 0 \\ & SH_{\mathrm{H}} \le 0 \\ & BE \ge 0 \end{aligned}$$

$$0 \le PE_{\mathrm{GT}} \le a_{GT_{\mathrm{E}}} BG_{\mathrm{GT}}^2 + b_{GT_{\mathrm{E}}} BG_{\mathrm{GT}} + c_{GT_{\mathrm{E}}} \tag{5}$$

$$0 \le PH_{\mathrm{GT}} \le a_{GT_{\mathrm{H}}} BG_{\mathrm{GT}}^2 + b_{GT_{\mathrm{H}}} BG_{\mathrm{GT}} + c_{GT_{\mathrm{H}}} \tag{6}$$

$$0 \le PH_{\mathrm{BA}} \le a_{\mathrm{BA}} BG_{\mathrm{BA}}^2 + b_{\mathrm{BA}} BG_{\mathrm{BA}} + c_{\mathrm{BA}} \tag{7}$$

$$BE + PE_{\mathrm{GT}} + SE_{\mathrm{E}} = DE \tag{8}$$

$$PH_{\mathrm{GT}} + PH_{\mathrm{BA}} + SH_{\mathrm{H}} = DH \tag{9}$$

$$BG = BG_{\mathrm{GT}} + BG_{\mathrm{BA}} \tag{10}$$

$$\underline{BG_{\mathrm{GT}}} \le BG_{\mathrm{GT}} \le \overline{BG_{\mathrm{GT}}} \tag{11}$$

$$\underline{BG_{\mathrm{BA}}} \le BG_{\mathrm{BA}} \le \overline{BG_{\mathrm{BA}}} \tag{12}$$

where the index for each factory agent is omitted, and $\underline{BG_{\mathrm{GT}}}$,

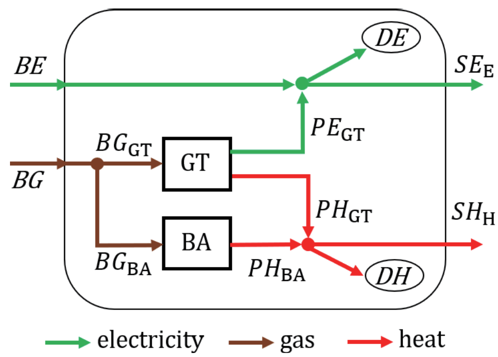

Fig. 2 Factory agent.

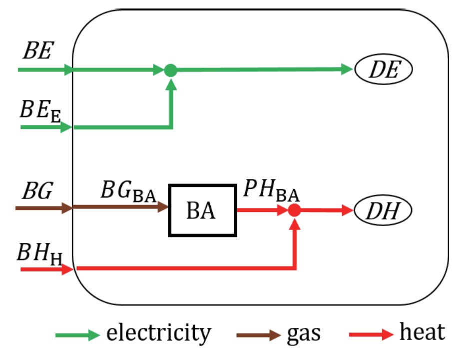

Fig. 3 Building agent.

$\overline{BG_{\rm GT}}$, $\underline{BG_{\rm BA}}$, and $\overline{BG_{\rm BA}}$ are given constants. Meaning of decision variables is given as follows:

- $SE_{\rm E}$, $SH_{\rm H}$: volumes of trading of electrical and thermal energy from inside of the district (if a factory is a supplier, then these are negative),
- BE, BG: volumes of electrical and thermal energy purchased from outside of the district,
- $BG_{\rm GT}$, $BG_{\rm BA}$: input energy of each equipment,
- $PE_{\rm GT}$, $PH_{\rm GT}$, $PH_{\rm BA}$: volumes of electrical and thermal energy generated by each equipment.

Meaning of constants is given as follows:

- α_{BE}, α_{BG}: unit price of electrical and thermal energy purchased from outside of district,
- $\alpha_{\rm E}$, $\alpha_{\rm H}$: unit price of electrical and thermal energy traded inside of district,
- DE, DH: electrical and thermal demands,
- $a_{\bullet}$, $b_{\bullet}$, $c_{\bullet}$: coefficients of input-output properties of equipments.

We remark here that x_i, $x_i^{\mathcal{M}}$, and α in Sect. 2 correspond to $[BE\ \ BG\ \ SE_{\rm E}\ \ SH_{\rm H}\ \ BG_{\rm GT}\ \ BG_{\rm BA}\ \ PE_{\rm GT}\ PH_{\rm GT}\ \ PH_{\rm BA}]^\top$, $[SE_{\rm E}\ \ SH_{\rm H}]^\top$, and $[\alpha_{\rm E}\ \ \alpha_{\rm H}]^\top$, respectively. (4) represents the energy cost. The first and second terms $\alpha_{BE}BE + \alpha_{BG}BG$ implies the amount paid to outside of the district. The third and fourth terms $\alpha_{\rm E}SE_{\rm E}+\alpha_{\rm H}SH_{\rm H}$ implies the amount paid to inside of the district. If a factory is a supplier, then $\alpha_{\rm E}SE_{\rm E} + \alpha_{\rm H}SH_{\rm H}$ is negative. Hence, minimization of (4) implies profit maximization in each agent. In addition, the objective function $f_i(x_i)$ in EP is given by $[\alpha_{BE}\ \ \alpha_{BG}\ \ \alpha_{\rm E}\ \ \alpha_{\rm H}\ \ 0_{1\times5}]x_i$. (5)–(7) represent input-output properties of equipments (due to solver limitation, input-output properties are represented by inequalities). (8)–(10) represent energy balances. (11) and (12) represent constraints for input energy.

Next, we explain a building agent (see also Fig. 3). Suppose that a building agent has a gas boiler (BA). The optimization problem for a building agent is given as follows:

$$
\begin{aligned}
\text{minimize}\quad & \alpha_{BE}BE + \alpha_{BG}BG + \alpha_{\rm E}BE_{\rm E} + \alpha_{\rm H}BH_{\rm H}\\
\text{subject to}\quad & BE_{\rm E} \geq 0\\
& BH_{\rm H} \geq 0\\
& BE \geq 0\\
& 0 \leq PH_{\rm BA} \leq a_{\rm BA}BG_{\rm BA}^2 + b_{\rm BA}BG_{\rm BA} + c_{\rm BA}\\
& BE + BE_{\rm E} = DE\\
& PH_{\rm BA} + BH_{\rm H} = DH\\
& BG = BG_{\rm BA}\\
& \underline{BG_{\rm BA}} \leq BG_{\rm BA} \leq \overline{BG_{\rm BA}}
\end{aligned}
$$

where the index for each building agent is omitted. Meaning of decision variables is given as follows:

- $BE_{\rm E}$, $BH_{\rm H}$: volumes of electrical and thermal energy purchased from inside of the district (If a building agent is a consumer, these are positive).

Other decision variables and constants are the same as those of a factory agent. We remark here that x_i and $x_i^{\mathcal{M}}$ in Sect. 2 correspond to $[BE\ \ BG\ \ BE_{\rm E}\ \ BH_{\rm H}\ \ BG_{\rm BA}\ \ PH_{\rm BA}]^\top$ and $[BE_{\rm E}\ \ BH_{\rm H}]^\top$, respectively. The objective function in the above problem implies the amount paid to outside/inside of the district. Hence, the above problem is a cost minimization problem. In addition, the objective function $f_i(x_i)$ in EP is given by $[\alpha_{BE}\ \ \alpha_{BG}\ \ \alpha_{\rm E}\ \ \alpha_{\rm H}\ \ 0_{1\times2}]x_i$.

Finally, since we consider two markets, the equality constraint (1) in Sect. 2 is given by

$$
\sum_{i=1}^{N_F}\begin{bmatrix} SE_{\rm E}^i \\ SH_{\rm H}^i \end{bmatrix} + \sum_{i=1}^{N_B}\begin{bmatrix} BE_{\rm E}^i \\ BH_{\rm H}^i \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix},
$$

where N_F and N_B are the number of factory and building agents, respectively, and i is the index for agents.

4. On-line Optimization Using Real-Time Demand Response

In this section, we propose an on-line optimization method using real-time DR.

4.1 Outline

First, we explain the outline of the proposed method. We suppose that hourly electrical and thermal demands planned in the previous day are given. Then, the optimization problem is solved every hour. Since the planned demand and the actual consumption are different, the difference between these values must be compensated in the future. In this paper, we suppose that this compensation is performed by DR. Based on the difference occurred at the current time, we modify the demand in the future. By this method, the hourly demand is changed, and it is expected that the total consumption in one day is almost the same as the total demand in one day.

4.2 Proposed Procedure

Let $DE^i(t)$ and $DH^i(t)$, $i = 1,2,\ldots,N_F + N_B$, $t = 0,1,2,\ldots,23$ denote hourly electrical and thermal demands planned in the previous day, respectively. We define

$$DE^i_{\text{total}} := \sum_{t=0}^{23} DE^i(t),$$
$$DH^i_{\text{total}} := \sum_{t=0}^{23} DH^i(t).$$

Let $DE^i_a(t)$ and $DH^i_a(t)$, $i = 1,2,\ldots,N_F + N_B$, $t = 0,1,2,\ldots,23$ denote hourly actual electrical consumption and hourly actual thermal consumption, respectively, where $DE^i_a(t)$ and $DH^i_a(t)$ corresponds to $DE^i(t)$ and $DH^i(t)$, respectively. Actual values of $DE^i_a(t)$ and $DH^i_a(t)$ can be measured by each agent. We also define the errors between the planned demand and the actual consumption as follows:

$$e^i_E(t) := DE^i(t) - DE^i_a(t),$$
$$e^i_H(t) := DH^i(t) - DH^i_a(t).$$

In the proposed method, the errors are distributed to the future planned demand. Let $l(t)$ denote the future time interval that the error at time t is distributed. The future time interval $l(t)$ is defined by

$$\begin{aligned} l(0) &= L, \\ l(1) &= L, \\ &\vdots \\ l(23-L) &= L, \\ l(23-L+1) &= L-1, \\ l(23-L+2) &= L-2, \\ &\vdots \\ l(23) &= 0, \end{aligned}$$

where L is a given non-negative integer. In addition, $\gamma_j(t) \geq 0$, $j = 0,1,2,\ldots,l(t)$ are given parameters that satisfy $\sum_{j=0}^{l(t)} \gamma_j(t) = 1$, where $\gamma_0(23) = 1$ holds.

Under these preparations, we propose the procedure for optimization using real-time demand response as follows.

Procedure for optimization using real-time demand response:
Step 0: Give $DE^i(t)$, $DH^i(t)$, $l(t)$, and $\gamma_j(t)$, $t = 0,1,2,\ldots,23$. Set $t = 0$.

Step 1: Solve the optimization problem EP using ADMM. First, the aggregate sends $\alpha(k)$ and $\bar{x}^{\mathcal{M}}(k)$ to each agent. Next, each agent solves (2). Finally, the aggregator collects $x_i^{\mathcal{M}}(k+1)$, calculates $\alpha(k+1)$ of (3), and sends $x_i^{\mathcal{M}}(k+1)$ to each agent. This procedure is repeated until the residual error is small.

Step 2: Apply the computation result to each agent. Each agent measures $DE^i_a(t)$ and $DH^i_a(t)$.

Step 3: Modify $DE^i(t+1+j)$ and $DH^i(t+1+j)$, $j = 0,1,\ldots,l(t)$ to

$$DE^i(t+1+j) \leftarrow DE^i(t+1+j) + \gamma_j(t) e^i_E(t), \quad (13)$$
$$DH^i(t+1+j) \leftarrow DH^i(t+1+j) + \gamma_j(t) e^i_H(t). \quad (14)$$

Step 4: Set $t \leftarrow t+1$. If $t = 24$, then the procedure is terminated. Otherwise, return to Step 1.

In the above procedure, the errors $e^i_E(t)$ and $e^i_H(t)$ are distributed to the future demand depending on $l(t)$ and $\gamma_j(t)$ given in advance. If the error is small, then DR will be successful at some level, and the effect of the past errors is suppressed. As a result, it is expected that the following relations on the total consumption in one day are achieved:

$$\sum_{t=0}^{23} DE^i_a(t) \approx DE^i_{\text{total}}, \quad (15)$$
$$\sum_{t=0}^{23} DH^i_a(t) \approx DH^i_{\text{total}}. \quad (16)$$

In the case where the error is large, then there is a possibility that DR does not work efficiently. This is because DR requests significant power savings for agents. It is one of the future efforts to consider applying the proposed method to such a case.

Remark 1: To realize the peak shift by DR, the total demand/consumption in one day is frequently focused (see, e.g., [7], [21]). In the proposed method, the peak shift may be realized by changing (13), (14) in consideration of the energy price. Further discussion is future work.

4.3 Implementation Using Blockchain

We consider implementing a distributed EMS using a blockchain. A blockchain is defined as "an open, distributed ledger that can record transactions between two parties efficiently and in a verifiable and permanent way" [10]. In a blockchain, a peer-to-peer network, which adheres to a protocol for inter-node communication and validates new blocks, manages typically. Figure 4 shows a distributed EMS using a blockchain. In the computer, the planned demand is calculated based on the past planned demand, the past actual consumption, information from power companies, and so on. The obtained planned demand is stored in the blockchain. Each agent reads the planned demand, α, and $\bar{x}^{\mathcal{M}}$, and solves the local optimization problem. A part of the computation result is stored in the blockchain,

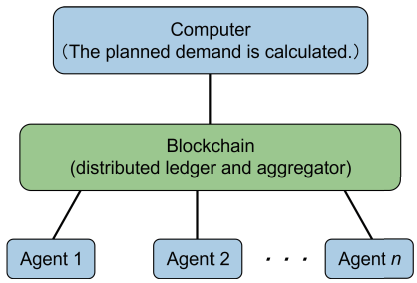

Fig. 4 Distributed EMS using a blockchain.

and is used in the update of α, and $\bar{x}^{\mathcal{M}}$. The actual consumption is also stored in the blockchain. In the blockchain, the future planned demand is modified based on the actual consumption (Step 3 in Sect. 4.2).

Using a blockchain, the information managed by the aggregator in ADMM is shared by all agents in the safe form that tamper is difficult. The function of the aggregator can be implemented by smart contracts on a blockchain. Smart contracts are simply programs stored on a blockchain (see, e.g., [5]). Using smart contracts, we do not need the aggregator that calculates $\alpha(k)$ and $\bar{x}^{\mathcal{M}}(k)$. We also calculate (13) and (14) in the blockchain†. On the other hand, the computation time is increased by introducing a blockchain (see [23] for further details). It is necessary to consider the trade-off between the safety and the computation time.

5. Numerical Example

In this section, a numerical example is presented.

We consider solving the optimization problem EP for the EMS in Sect. 3 with real-time demand response. Consider the EMS that is composed of two factory agents (F1, F2) and three building agents (B1, B2, B3). Table 1 shows the energy price from outside of the district. Table 2 shows the parameters of each agent. Figure 5 and Fig. 6 show hourly electrical demand and hourly thermal demand planned in the previous day, respectively. The parameters and energy demands are generated based on the references [18], [19].

In numerical experiments, we use a private Ethereum blockchain network [27]. We also use Python/CVXpy [8] to solve the local optimization problem. Remote procedure calls through EthJsonRpc allow the Python scripts to communicate with the smart contracts. The computer with CPU: Core i7-8086K, Memory: 16 GB is used.

The parameter ρ in ADMM is set to 0.1. If both $\sum_{i\in\mathcal{I}} x_i^{\mathcal{M}}(k) < \varepsilon$ and $\rho(k+1)(x^{\mathcal{M}}(k+1) - x^{\mathcal{M}}(k)) < \varepsilon$ are satisfied, then the computation procedure is terminated. In this example, we set $\varepsilon = 0.005$. The initial values of α_{E} and α_{H} are given by zero. In addition, the parameter L in the definition of $l(t)$ is given by 0 (i.e., $\gamma_0(t) = 1$).

We explain the computation results. In this numerical example, $DE_a^i(t)$ and $DH_a^i(t)$ are given as follows:

†Each agent may calculate (13) and (14). The modified planned demand is stored in the blockchain.

Table. 1 Energy price from outside of the district.

		Price
α_{BE}	$[10^3\text{JPY/MWh}]$	10.39
α_{BG}	$[10^3\text{JPY}/10^2\text{m}^3]$	2.86

Table. 2 Parameters.

		F1	F2	B1	B2	B3
$a_{GT_{\mathrm{E}}}$	[-]	−0.001	−0.002	-	-	-
$b_{GT_{\mathrm{E}}}$	[-]	0.52	0.51	-	-	-
$c_{GT_{\mathrm{E}}}$	[-]	−2.0	−2.5	-	-	-
$a_{GT_{\mathrm{H}}}$	[-]	−0.001	−0.007	-	-	-
$b_{GT_{\mathrm{H}}}$	[-]	0.78	1.3	-	-	-
$c_{GT_{\mathrm{H}}}$	[-]	−3.3	−6.0	-	-	-
$\overline{BG}_{\mathrm{GT}}$	$[10^2\text{m}^3]$	46.4	27.5	-	-	-
$\underline{BG}_{\mathrm{GT}}$	$[10^2\text{m}^3]$	5.83	5.55	-	-	-
a_{BA}	[-]	−0.4	−0.4	−0.5	−0.45	−0.4
b_{BA}	[-]	5.1	4.95	5.0	4.9	4.95
c_{BA}	[-]	−1.0	−1.0	−0.5	−0.5	−1.0
$\overline{BG}_{\mathrm{GT}}$	$[10^2\text{m}^3]$	2.75	1.36	1.84	1.63	2.18
$\underline{BG}_{\mathrm{GT}}$	$[10^2\text{m}^3]$	0.405	0.23	0.12	0.14	0.18

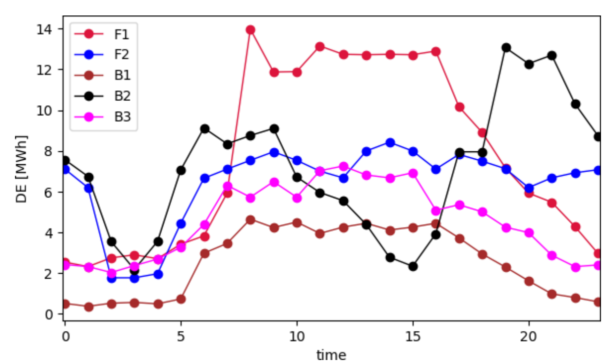

Fig. 5 Electrical demand planned in the previous day.

$$DE_a^i(t) = DE^i(t) + v(t),$$
$$DH_a^i(t) = DH^i(t) + w(t),$$

where $v(t)$ and $w(t)$ are the uniform distribution noise in the ranges $[0, 0.05\mathrm{DE}^i(t)]$ and $[0, 0.05\mathrm{DH}^i(t)]$, respectively.

First, we validate the effectiveness of the proposed method. Figure 7 and Fig. 8 show hourly electrical consumption $DE_a^i(t)$ and hourly thermal consumption $DH_a^i(t)$ with and without the proposed method, respectively. When the proposed method is not used, the future demand is not changed. As a result, consumption sometimes increases. From Fig. 7 and Fig. 8, we see that this fact holds. Table 3 and Table 4 show the total demand and consumption of electrical energy and thermal energy in one day. From these results, we see that the relations (15) and (16) are achieved by using the proposed method.

In addition, we also discuss the optimal value of the objective function for each agent. Table 5 shows the averages of $DE^i(t)$, $DH^i(t)$, and the optimal value of the objective function f_i at each time. From this table, we see that comparing between F1 and B2, the average demand is similar, but the average of the optimal value of f_i (i.e., the energy cost) is different. Because the energy cost of F1 includes the

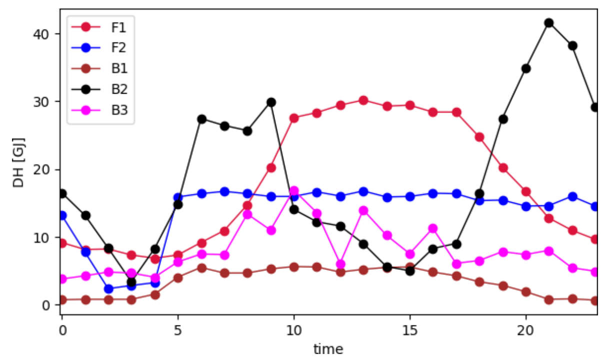

Fig. 6 Thermal demand planned in the previous day.

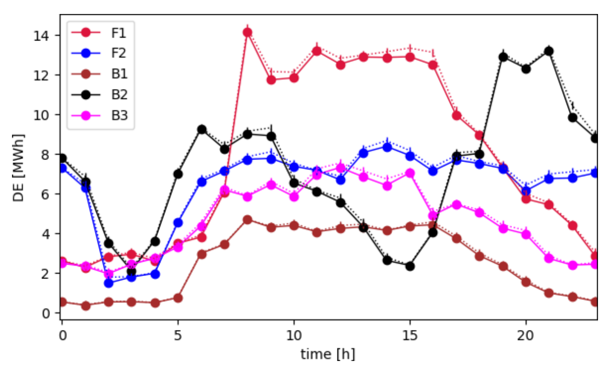

Fig. 7 Electrical consumption. Solid line: Using the proposed method. Dotted line: Not using the proposed method.

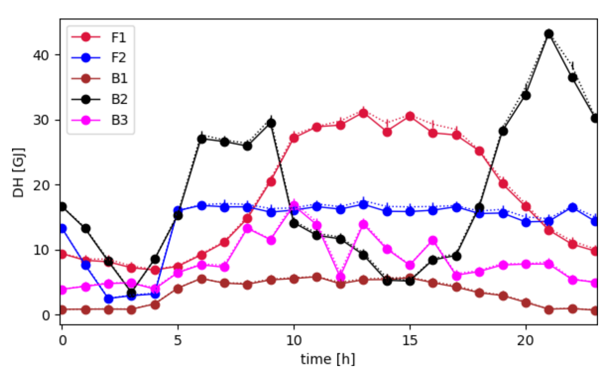

Fig. 8 Thermal consumption. Solid line: Using the proposed method. Dotted line: Not using the proposed method.

Table. 3 Total demand and consumption of electrical energy in one day.

	F1	F2	B1	B2	B3
DE^i_{total}	185.9	154.4	61.2	170.5	109.5
$\sum_{t=0}^{23} DE^i_a(t)$ with real-time DR	185.9	154.6	61.2	170.8	109.7
$\sum_{t=0}^{23} DE^i_a(t)$ without real-time DR	190.4	158.6	62.6	174.6	112.8

profit obtained by selling the energy to other agents.

Next, we comment about the effects of tampering and advantages of implementing the proposed method using a blockchain. We suppose here that the sign of the error is tampered. That is, we suppose that (13) and (14) are tampered as follows:

Table. 4 Total demand and consumption of thermal energy in one day.

	F1	F2	B1	B2	B3
DH^i_{total}	428.0	331.1	81.0	436.3	193.1
$\sum_{t=0}^{23} DH^i_a(t)$ with real-time DR	428.4	331.5	81.0	437.5	193.1
$\sum_{t=0}^{23} DH^i_a(t)$ without real-time DR	437.5	340.2	83.2	446.0	197.4

Table. 5 Averages of $DE^i(t)$, $DH^i(t)$, and the optimal value of the objective function f_i at each time.

	F1	F2	B1	B2	B3
DE^i	7.7	6.4	2.6	7.1	4.6
DH^i	17.8	13.8	3.4	18.2	8.0
f_i	36.0	46.4	26.7	68.6	46.5

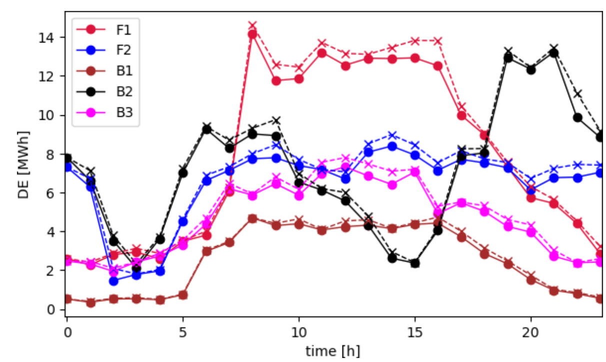

Fig. 9 Electrical consumption. Solid line: The normal case. Dashed line: The case of tampering.

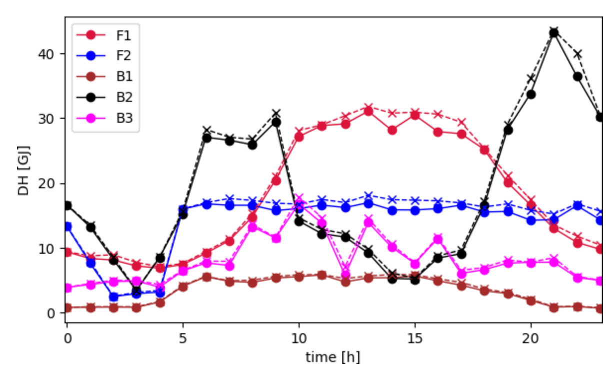

Fig. 10 Thermal consumption. Solid line: The normal case. Dashed line: The case of tampering.

$$DE^i(t+1+j) \leftarrow DE^i(t+1+j) - \gamma_j(t)e^i_E(t),$$
$$DH^i(t+1+j) \leftarrow DH^i(t+1+j) - \gamma_j(t)e^i_H(t).$$

Figure 9 and Fig. 10 show hourly electrical consumption $DE^i_a(t)$ and hourly thermal consumption $DH^i_a(t)$ in the normal case and in the case of tampering. Since the sign of the error is changed, the future demand is not suppressed, and sometimes becomes larger. As a result, the actual consumption sometimes becomes larger. From Fig. 9 and Fig. 10, we see that this fact holds. Using a blockchain, we can prevent such cases of tampering.

Finally, we comment about the computation time. In this example, the optimization problem EP is solved 24 times. In the case where a blockchain is not used, the worst and mean computation times of EP were 29 sec and 10 sec, respectively. In the case where a blockchain is used, the worst and mean computation times of EP were 800 sec and 252 sec, respectively. Thus, the blockchain technology provides tamper-resistant properties, but requires the long computation time. Since EP should be solved within one hour, this computation result suggests the proposed method can be applied to a distributed EMS.

6. Conclusion

In this paper, we considered a blockchain-based optimization method for a distributed EMS considering both electrical energy and thermal energy. We supposed that the difference between the planned demand and the modified demand is compensated by DR. The effectiveness of the proposed method was presented by a numerical example. By a numerical example, we also discussed the adverse effect of tampering.

In future work, it is important to apply the proposed method to a more practical situation. In addition, there is a possibility that the energy costs for some agents relatively increase. It is also one of the future efforts to consider the equitability between agents.

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