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PAPER

Autonomous Decentralized Mechanism for Energy Interchanges with Accelerated Diffusion Based on MCMC

Yusuke SAKUMOTO[†a)] ***and*** **Ittetsu TANIGUCHI**[††b)]**,** ***Members***

SUMMARY It is not easy to provide energy supply based on renewable energy enough to satisfy energy demand anytime and anywhere because the amount of renewable energy depends on geographical conditions and the time of day. In order to maximize the satisfaction of energy demand by renewable energy, surplus energy generated with renewable energy should be stored in batteries, and transmitted to electric loads with high demand somewhere in the electricity system. This paper proposes a novel autonomous decentralized mechanism of energy interchanges between distributed batteries on the basis of the diffusion equation and MCMC (Markov Chain Monte Carlo) for realizing energy supply appropriately for energy demand. Experimental results show that the proposed mechanism effectively works under several situations. Moreover, we discuss a method to easily estimate the behavior of the entire system by each node with the proposed mechanism, and the application potentiality of this estimating method to an efficient method working with non-renewable generators while minimizing the dependence of non-renewable energy, and an incentive mechanism to prevent monopolizing energy in systems.

key words: *renewable energy, microgrid, autonomous decentralized control, power routing*

1. Introduction

Renewable energy (e.g., sunlight and wind) is hoped to be alternative energy of the conventional fuel (e.g., fossil fuel and nuclear fuel). Since the amount of renewable energy depends on geographical conditions and the time of day, the energy supply based on the renewable energy cannot be provided enough to satisfy energy demand at some times and locations. Thus, it is important challenge for renewable energy to develop an effective method of the energy supply appropriately for energy demand.

In order to prevent wasting renewable energy, surplus energy generated with renewable energy should be stored in batteries, and transmitted to electric loads with high demand somewhere in the electricity system. Microgrid [1]–[3], which is an electricity system interconnecting distributed batteries, would be a key technology to provide such the effective way for surplus energy interchanges.

Some works [4]–[8] are proceeding with energy interchanges between distributed batteries for realizing the energy supply appropriately for energy demand in a microgrid. Taniguchi et al. proposed an energy trading algorithm for energy interchanges on the basis of machine learning [5]. The algorithm supposes a virtual energy market to trade surplus energy between distributed batteries in a microgrid, and performs energy interchanges using energy routing (see Fig. 1 (left)) based on the trades in the virtual energy market. By using the energy trading, the algorithm balances energy supply and demand of each node, and consequently provides the energy supply appropriately for energy demand. However, since such the energy market is a kind of centralized management system, any energy interchanges cannot be performed if the energy market is down. Hence, energy interchanges should be realized by only using autonomous decentralized manner. Therefore, we will design a method of energy interchanges without any centralized management system (see Fig. 1 (right)).

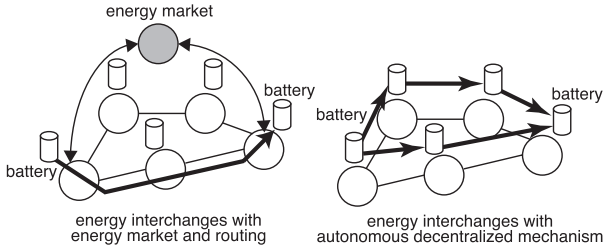

Fig. 1 Energy interchanges with energy market and routing (left) and autonomous decentralized mechanism (right).

In a physical system, when ink spills into water, particles composing the ink are diffused throughout the water over time until particle densities are eventually uniformed without supposing any centralized entity. This phenomenon can be described by the diffusion equation. If the difference between energy supply and demand in a microgrid could be diffused like the particle density, the energy supply appropriately for energy demand would be realized using autonomous decentralized manner.

This paper proposes a novel autonomous decentralized mechanism of energy interchanges based on the diffusion equation for energy supply appropriately for energy demand in microgrids. The diffusion equation represents the local interaction between differential volume elements in a physical system, and so it can be converted into the local interaction between adjacent nodes without necessity of any centralized management system [9] (see Fig. 2), which achieves high robustness for disasters. We first derive an expression of the energy interchange amount between batteries of an adjacent node pair on the basis of the diffusion equation, and then

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[†]The author is with Tokyo Metropolitan University, Hino-shi, 191-0065 Japan.
[††]The author is with Ritsumeikan University, Kusatsu-shi, 525-0058 Japan.
a) E-mail: sakumoto@tmu.ac.jp
b) E-mail: i-tanigu@fc.ritsumei.ac.jp
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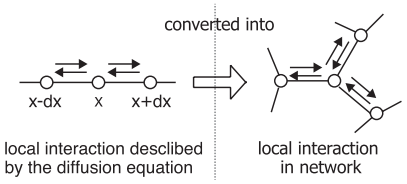


Fig. 2 The conversion from the local interaction described in the diffusion equation to the local interaction in a network.

speed up the derived expression by using MCMC (Markov Chain Monte Carlo). Moreover, we visually confirm the effectiveness of the proposed mechanism, and quantitatively investigate the speed of balancing energy supply and demand with the proposed mechanism under several situations. Finally, we discuss a method to easily estimate the behavior of the entire system by each node with the proposed mechanism, and the application potentiality of this estimating method to an efficient method working with non-renewable generators while minimizing the dependence of non-renewable energy, and an incentive mechanism to prevent monopolizing energy in systems.

This paper is organized as follows: Section 2 describes the system model, and Sect. 3 shows the proposed mechanism. Experimental results are described in Sect. 4. Section 5 discusses the extensibility of our proposed mechanism. Section 6 oncludes this paper.

2. System Model

We use a simple microgrid model to discuss fundamental properties of the proposed mechanism. The definition of symbols of the system model is shown in Table 1.

The system has network $G = (V, E)$ where V and E are sets of nodes and links. Each node has electric equipment (i.e., a energy generator, a battery, and one or more loads), and can transmit energy to batteries of other nodes connected with a link in E. Let a_i be the set of nodes connected to node i. We call nodes in a_i "adjacency nodes". To discuss fundamental properties, we assume that network G is stationary and connected.

We denote the remaining battery amount and the energy demand of node i by $q_i(t)$ and θ_i, respectively. We define a metric for the difference between energy supply and demand at node i by sufficiency level $\hat{q}_i(t)$, which is given by

$$\hat{q}_i(t) := q_i(t) - \theta_i. \tag{1}$$

Node i can know whether its adjacent nodes j need more energy by the observation of $\hat{q}_j(t)$ ($j \in a_i$). If $\hat{q}_i(t) = \hat{q}_j(t)$ for all node pairs (i, j), the energy supply would be performed appropriately for the energy demand of nodes at time t.

To uniform sufficiency levels of all nodes, each node transmits its energy to batteries of adjacent nodes until $\hat{q}_i(t) = \hat{q}_j(t)$ for all node pairs (i, j) are fulfilled. Every ΔT_J, node i autonomously gathers sufficiency levels $\hat{q}_j(t)$ from

Table 1 Definition of symbols.

	energy transmission network G
V	set of nodes
E	set of links
N	number of nodes
	node i
a_i	set of adjacency nodes
b_i	battery capacity
θ_i	energy demand
$g_i(t)$	generated energy at time t
$c_i(t)$	consumed energy at time t
$q_i(t)$	remaining battery amount at time t
$\hat{q}_i(t)$	sufficiency level at time t
$J_{i\to j}(t)$	energy interchange amount to node j at time t
$o_i(t)$	amount of overrun at time t
$u_i(t)$	amount of underrun at time t
	proposed mechanism
k'	diffusion coefficient
κ'	parameter used in Eq. (12)
ΔT_J	update interval of $J_{i\to j}(t)$

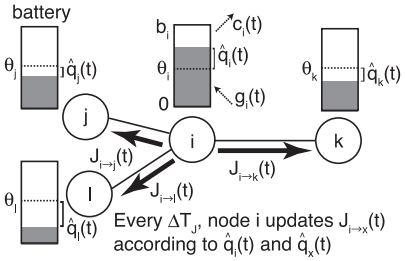


Fig. 3 The energy interchanges of node i.

adjacent nodes, and calculates energy interchange amount $J_{i\to j}(t)$. Node i transmits $J_{i\to j}(t)$ to the battery of adjacent nodes j. Figure 3 illustrates the energy interchanges of node i in the system model.

Let $g_i(t)$ and $c_i(t)$ be the generated energy and the consumed energy of node i. The evolution of remaining battery amount $q_i(t)$ of node i is given by

$$\begin{aligned} q_i(t + \Delta T_J) - q_i(t) = &\int_t^{t+\Delta T_J} (g_i(t) - c_i(t))dt \\ &+ \sum_{j\in a_i} (J_{j\to i}(t) - J_{i\to j}(t)). \end{aligned} \tag{2}$$

Note that we assume any energy loss of battery-to-battery charging can be ignored.

3. Autonomous Decentralized Mechanism for Energy Interchanges

3.1 Basic Idea

We derive the expression of energy interchange amount $J_{i\to j}(t)$ for uniforming all sufficiency levels on the basis of the diffusion equation. The diffusion equation describes the dynamics of particle density $y(t, \boldsymbol{X})$, and is given by

$$\frac{\partial y(t, \boldsymbol{X})}{\partial t} = k \triangle y(t, \boldsymbol{X}), \tag{3}$$

where $\boldsymbol{X}$ is a positional vector, k is the diffusion coefficient, and $\triangle$ is the Laplace operator. The diffusion process given by Eq. (3) continues until $\triangle y(t, \boldsymbol{x}) = 0$, which corresponds to a uniformed state for particle density $y(t, \boldsymbol{X})$. Hence, it ensures that particle density $y(t, \boldsymbol{X})$ is uniformed with Eq. (3). The diffusion equation represents the local interaction between differential volume elements, and so it can approximately converted to the local interaction between adjacency nodes in a network. Hence, we can derive the expression of energy interchange amount $J_{i\to j}(t)$ in our autonomous decentralized mechanism. Moreover, the diffusion equation conserves the sum of the particle densities, and so the derived expression of $J_{i\to j}(t)$ can avoid any energy loss in the calculation of energy interchange amounts.

The faster uniforming $\hat{q}_i(t)$ is better for appropriate energy supply. However, since Eq. (3) is a linear equation if k is constant, it is slow to converge to a uniformed state. To speed up the uniforming $\hat{q}_i(t)$ with Eq. (3), we derive a non-linear diffusion equation on the basis of MCMC (Markov Chain Monte Carlo), and the improved expression of $J_{i\to j}(t)$ corresponding to the non-linear diffusion equation. Moreover, we will prove that the improved expression of $J_{i\to j}(t)$ can guarantee the uniforming $\hat{q}_i(t)$ as well as the original expression.

3.2 Expression of Energy Interchange Amount $J_{i\to j}(t)$

First, we derive the expression of energy interchange amount $J_{i\to j}(t)$ based on the diffusion equation. To obtain the expression from Eq. (3), we not only replace y with $\hat{q}$, but also determine the calculation way of $\triangle$. If the coordinate system for positional vector $\boldsymbol{X}$ can be defined, $\triangle$ should be calculated with the same way in the physics. However, in network G, a coordinate system cannot be defined because each node has a different number of its adjacent nodes. Hence, we define the calculation way of $\triangle$ in network G with considering its significance, which is the sum of differences in its surroundings. Therefore, in network G, instead of Eq. (3), we use the following discrete diffusion equation of sufficiently level $\hat{q}_i(t)$

$$\hat{q}_i(t + \Delta T_J) - \hat{q}_i(t) = k' \Delta T_J \sum_{j\in a_i} (\hat{q}_j(t) - \hat{q}_i(t)), \tag{4}$$

where k' is the diffusion coefficient corresponding to k in Eq. (3). Note that $k' \Delta T_J$ should be small enough to stably calculate Eq. (4). According to [10], $k' \Delta T_J$ should be set in $0 < k' \Delta T_J < 1/\max(|a_i|)$ for all i. Equation (4) is also used in a model of water supply systems [11]. One can confirm that the diffusion process given by Eq. (4) also continues a uniformed state for sufficiency level $\hat{q}_i(t)$.

According to Eq. (4), the expression of energy interchange amount $J_{i\to j}(t)$ for uniforming $\hat{q}_i(t)$ is given by

$$J_{i\to j}(t) = k' \Delta T_J \hat{q}_i(t). \tag{5}$$

With Eq. (5), energy interchange amounts do not depend on sufficiency levels of adjacency nodes. However, the uniforming sufficiency levels would be faster when using $J_{i\to j}(t)$ appropriately for sufficiency level $\hat{q}_j(t)$ of adjacency node j. In other words, energy interchange amount $J_{i\to j}(t)$ for node pair (i, j) with a larger difference between $\hat{q}_i(t)$ and $\hat{q}_j(t)$ should be larger than other energy interchange amounts for decreasing the variance of sufficiency levels. Hence, the proposed mechanism does not use the expression (5) derived from Eq. (4). The proposed mechanism uses the expression based on MCMC discussed on the following paragraphs.

To obtain the expression for fast uniforming $\hat{q}_i$, we consider the following non-linear diffusion equation

$$\hat{q}_i(t + \Delta T_J) - \hat{q}_i(t) = k' f_{i\to j}(\hat{q}_i(t), \hat{q}_j(t)) \Delta T_J \sum_{j\in a_i} (\hat{q}_j(t) - \hat{q}_i(t)), \tag{6}$$

and the corresponding expression of energy interchange amount $J_{i\to j}(t)$ is given by

$$J_{i\to j}(t) = k' \Delta T_J f_{i\to j}(\hat{q}_i(t), \hat{q}_j(t)) \hat{q}_i(t), \tag{7}$$

where $f_{i\to j}(\hat{q}_i(t), \hat{q}_j(t))$ is a non-constant coefficient that is the difference between Eqs. (4) and (7).

On the basis of MCMC, we derive $f_{i\to j}(\hat{q}_i(t), \hat{q}_j(t))$ for fast decreasing the variance of sufficiency levels. MCMC is a method for the probability distribution of a metric. In [12], the probability distribution of the Hamiltonian in a ferromagnetism model (Ising spin model) is controlled by using MCMC. In this paper, we apply MCMC to control the probability distribution of variances of sufficiency levels for fast uniforming sufficiency levels.

We define variance $\mathrm{Var}(\hat{\boldsymbol{Q}}(t))$ of sufficiency levels as

$$\mathrm{Var}(\hat{\boldsymbol{Q}}(t)) = \frac{1}{|V|} \sum_{i=1}^{|V|} (\hat{q}_i(t) - \mathrm{E}(\hat{\boldsymbol{Q}}))^2, \tag{8}$$

where $\hat{\boldsymbol{Q}}(t) = (\hat{q}_1(t), \hat{q}_2(t), ..., \hat{q}_{|V|}(t))$, and $\mathrm{E}(\hat{\boldsymbol{Q}}(t))$ is the average of sufficiency levels, which is given by

$$\mathrm{E}(\hat{\boldsymbol{Q}}(t)) = \frac{1}{|V|} \sum_{i=1}^{|V|} \hat{q}_i(t). \tag{9}$$

If sufficiency levels are uniformed, $\mathrm{Var}(\hat{\boldsymbol{Q}}(t)) = 0$.

We can control the probability distribution of variance $\mathrm{Var}(\hat{\boldsymbol{Q}}(t))$ by appropriately deriving the transition probability of a state transition regarding sufficiency levels on the basis of MCMC. Here, we consider the state transition corresponding to the moving of the amount $\Delta\hat{q}$ of the sufficiency level from node i to node j ($j \in a_i$), and denote the transition probability of the state transition by $p(\Delta\hat{q}|i \to j)$. We can control the probability distribution of variance $\mathrm{Var}(\hat{\boldsymbol{Q}}(t))$ to $\exp\left[-\lambda \mathrm{Var}(\hat{\boldsymbol{Q}}(t))\right]$ if transition probability $p(\Delta\hat{q}|i \to j)$ satisfies the following condition

$$\exp\left[-\lambda \mathrm{Var}(\hat{\boldsymbol{Q}}(t))\right] p(\Delta\hat{q}|i \to j) = p(\Delta\hat{q}|i \to j) \exp\left[-\lambda \mathrm{Var}(\hat{\boldsymbol{Q}}'(t))\right], \tag{10}$$

where λ is a positive parameter ($\lambda > 0$), and $\mathrm{Var}(\hat{\boldsymbol{Q}}'(t))$ is the variance after the state transition. Probability distribution $\exp[-\lambda x]$ is a monotonically decreasing function, and so it is suitable for decreasing the variance.

According to MCMC, transition probability $p(\Delta\hat{q}|i \to j)$ satisfying the condition (10) is given by

$$p(\Delta\hat{q}|i \to j) = \begin{cases} 1 & \text{if } \Delta\mathrm{Var}_{i\to j}(\hat{\boldsymbol{Q}}(t)) < 0 \\ \exp\left[-\lambda \Delta\mathrm{Var}_{i\to j}(\hat{\boldsymbol{Q}}(t))\right] & \text{otherwise} \end{cases} \approx 1 - \lambda \left[\Delta\mathrm{Var}_{i\to j}(\hat{\boldsymbol{Q}}(t))\right]^+, \tag{11}$$

where $[x]^+ = \max(0, x)$, and $\Delta\mathrm{Var}_{i\to j}(\hat{\boldsymbol{Q}}(t))$ is the difference between $\mathrm{Var}(\hat{\boldsymbol{Q}}(t))$ and $\mathrm{Var}(\hat{\boldsymbol{Q}}'(t))$. To derive Eq. (11), we use the first-order Taylor series approximation. Difference $\Delta\mathrm{Var}_{i\to j}(\hat{\boldsymbol{Q}}(t))$ is given by

$$\begin{aligned} \Delta\mathrm{Var}_{i\to j}(\hat{\boldsymbol{Q}}(t)) &= \mathrm{Var}(\hat{\boldsymbol{Q}}'(t)) - \mathrm{Var}(\hat{\boldsymbol{Q}}(t)) \\ &= 2(\hat{q}_j(t) - \hat{q}_i(t) + \Delta q)\Delta q \\ &\approx 2\kappa \left|\hat{q}_j(t) - \hat{q}_i(t)\right| (\hat{q}_j(t) - \hat{q}_i(t)), \end{aligned} \tag{12}$$

where $\Delta q = \kappa|\hat{q}_j(t) - \hat{q}_i(t)|$ ($\kappa \ll 1$). Energy interchange amount $J_{i\to j}(t)$ is also given by $p(\Delta\hat{q}|i \to j)\,\hat{q}_i(t)$, and so we derive the following expression

$$\begin{aligned} f_{i\to j}(\hat{q}_i(t), \hat{q}_j(t)) &= p(\Delta\hat{q}|i \to j) \\ &= 1 - \lambda[\Delta\mathrm{Var}_{i\to j}(\hat{\boldsymbol{Q}}(t))]^+ \\ &= 1 - 2\,\lambda\,\kappa \left|\hat{q}_j(t) - \hat{q}_i(t)\right| (\hat{q}_j(t) - \hat{q}_i(t))^+ \\ &= 1 - \kappa' \left|\hat{q}_j(t) - \hat{q}_i(t)\right| (\hat{q}_j(t) - \hat{q}_i(t))^+. \end{aligned} \tag{13}$$

Although $\kappa \ll 1$, κ' can be set to a value larger than one because of $\kappa' = 2\,\lambda\,\kappa$.

When using non-constant coefficient $f_{i\to j}(\hat{q}_i(t), \hat{q}_j(t))$ given by Eq. (13), the uniforming $\hat{q}_i$ becomes faster. According to MCMC, we derive Eq. (13) for controlling the probability distribution of variance $\mathrm{Var}(\hat{\boldsymbol{Q}}(t))$ to $\exp\left[-\lambda\,\mathrm{Var}(\hat{\boldsymbol{Q}}(t))\right]$. As λ increases, the average of variance $\mathrm{Var}(\hat{\boldsymbol{Q}}(t))$ decreases. If $\lambda = 0$, Eq. (7) is equivalent to Eq. (5) because $f_{i\to j}(\hat{q}_i(t), \hat{q}_j(t)) = 1$. Hence, the variance when using Eq. (7) is always smaller than that when using Eq. (5). Therefore, we can also uniform sufficiency levels by using Eqs. (7) and (13), and the speed for uniforming becomes faster.

3.3 Avoiding Overrun and Underrun of a Battery

In the proposed mechanism, node i transmits its remaining battery amount only according to sufficiency levels. Hence, overrun (i.e., $q_i(t) > b_i$) and underrun (i.e., $q_i(t) < 0$) would occur. If node i predicts overrun and underrun by its energy transmission, it should appropriately change $J_{i\to j}(t)$ to avoid them.

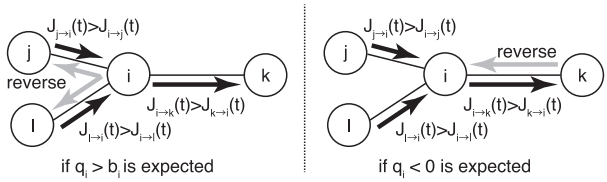


Fig. 4 Procedure for preventing the overrun and underrun of node energy $q_i(t)$.

The amounts $o_i(t)$ and $u_i(t)$ of overrun and underrun by the energy interchange of node i are given by

$$o_i(t) = \left[\hat{q}_i + \Delta T_J \sum_{j\in a_i} \Big(J_{j\to i}(t) - J_{i\to j}(t)\Big) + \theta_i - b_i\right]^+, \tag{14}$$

$$u_i(t) = \left[\hat{q}_i + \Delta T_J \sum_{j\in a_i} \Big(J_{j\to i}(t) - J_{i\to j}(t)\Big) + \theta_i\right]^-, \tag{15}$$

where $[x]^- = \min(0, x)$.

To avoid the overrun and underrun with $o_i(t)$ and $u_i(t)$, respectively, node i changes energy interchange amount $J_{i\to j}(t)$ to $J_{i\to j}(t) + \Delta J^{(o)}_{i\to j}(t) + \Delta J^{(u)}_{i\to j}(t)$. The differences $\Delta J^{(o)}_{i\to j}(t)$ and $\Delta J^{(u)}_{i\to j}(t)$ are given by

$$\Delta J^{(o)}_{i\to j}(t) = \frac{\left[J_{j\to i}(t) - J_{i\to j}(t)\right]^+}{\sum_{k\in a_i}\left[J_{j\to i}(t) - J_{i\to j}(t)\right]^+} \frac{o_i(t)}{\Delta T_J}, \tag{16}$$

$$\Delta J^{(u)}_{i\to j}(t) = \frac{\left[J_{i\to j}(t) - J_{j\to i}(t)\right]^+}{\sum_{k\in a_i}\left[J_{i\to j}(t) - J_{j\to i}(t)\right]^+} \frac{u_i(t)}{\Delta T_J}. \tag{17}$$

We illustrate the above procedures in Fig. 4.

4. Evaluation

Through simulation experiments, we clarify the effectiveness of the proposed mechanism. The goal of the proposed mechanism is to uniform sufficiency levels of nodes for the energy supply appropriately for the energy demand of nodes. We visually confirm that the proposed mechanism achieves the goal, and quantitatively investigate the uniforming speed of the proposed mechanism under several situations.

4.1 Setting

We use a basic model for easily understanding fundamental properties of the proposed mechanism. In a real system, there are several factors affecting the geographical heterogeneity. However, we represent the geographical heterogeneity only by the heterogeneity of initial energies $q_i(0)$. We assume (a) the generated energy $g_i(t)$ of node i is always equal to the consumed energy $c_i(t)$, and (b) demand amount

θ_i of node i does not vary with time. Under situations without the assumption, we will confirm the effectiveness of the proposed mechanism in the future work.

Initially, energy $g_i(0)$ of node i is given by Normal distribution $\mathrm{N}(\mu_q^{\mathrm{st}}, \sigma_q^{\mathrm{st}})$. The variation of sufficiency levels at $t = 0$ represents the initial geographical heterogeneity. All nodes would be sufficient after the uniforming $\hat{q}_i(t)$ if we give the initial energies according to the following condition

$$\mu_q^{\mathrm{st}} > \frac{1}{N}\sum_{i=1}^{N}\theta_i. \tag{18}$$

By changing the value of μ_q^{st}, we can generate several situations (e.g., energy shortage and surplus situations) in simulation.

During simulation, each node transmits own energy according to the proposed mechanism (hereafter referred to as *proposal mechanism*) or the mechanism with Eq. (5) (hereafter referred to as *diffusion mechanism*).

We use the N_k-th nearest neighbor network as network G. The N_k-th nearest neighbor network is generated by the following procedures. Initially, each node is randomly placed on the two dimensional plane. Then, each node selects N_k nearest nodes as its adjacent nodes. Note that a node has adjacent nodes greater than or equal to N_k. N_k-th nearest neighbor network is a network with considering geographical dispersion of nodes and wiring cost between nodes. We also use the two-dimensional lattice grid network for a baseline network because it is a homogeneous network where all nodes have four adjacent nodes. In a two-dimensional lattice grid network, all nodes are regularly placed in the two dimensional plane with the periodic boundary condition. Figure 5 shows examples of 5-th nearest neighbor network and two-dimensional lattice grid network for $N = 100$, respectively.

We use the parameter configuration shown in Table 2 as a default parameter configuration.

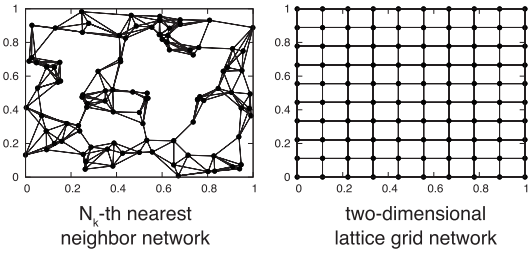


Fig. 5 Examples of N_k-th nearest neighbor network ($N_k = 5$, $N = 100$) and two-dimensional lattice grid network ($N = 100$).

4.2 Result

First, we visually confirm the effectiveness of the proposal mechanism. Figure 6 illustrates the color bar corresponding to a value for visualized results.

Figures 7(a) through (c) show the geographical distributions of node energies at $t = 0$, 250, and 500. In this simulation, the average of initial energies for nodes in the central region ($1/3 < x < 2/3$ and $1/3 < y < 2/3$) of the $x - y$ plane is set to 5, and the average of initial energies for other nodes is set to 50. According to these figures, we confirm that the proposal mechanism can supply energies to the nodes in the central region.

Figure 8 shows time evolution of statistics (i.e., maximum, average, and minimum) of node energies when the initial energies shown in Fig. 7(a). In this figure, we show the results of the proposal mechanism and the diffusion mechanism for comparison. The proposal mechanism can uniform node energies faster compared with the diffusion mechanism. In particular, it has high effectiveness for fast supplying the energy into nodes with severe energy short-

Table 2 Parameter configuration.

network	G	N_k-nearest neighbor network
number of nearest nodes	N_k	5
number of nodes	N	400
battery capacity of a node	b_i	100
electric demand amount of a node	θ_i	50
diffusion coefficient	k'	0.0001
parameter in Eq. (11)	κ'	1000
interval of recalculating $J_{i\to j}$	ΔT_J	1
average of initial energies	μ_q^{st}	50
standard variance of initial energies	σ_q^{st}	$k_\sigma \mu_q^{\mathrm{st}}$
coefficient of standard variances	k_σ	0.3

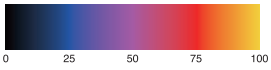
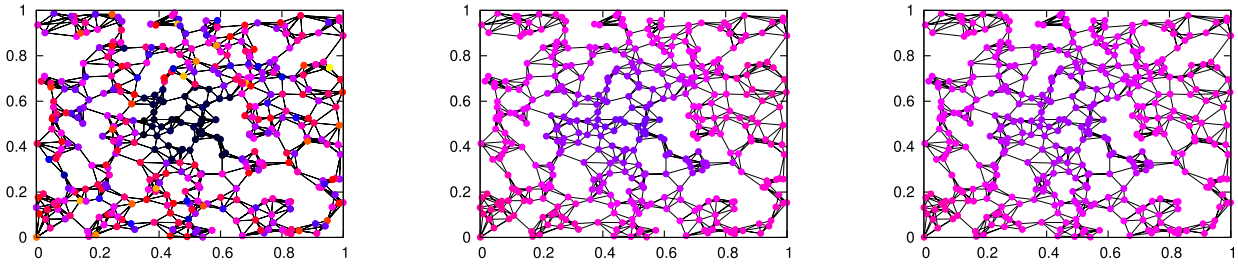


Fig. 6 Color bar corresponding to a value for Figs. 7 and 9.



(a) $t = 0$ (b) $t = 250$ (c) $t = 500$

Fig. 7 Geographical distributions of node energies $q_i(t)$.

age. This result would indicate that the proposed mechanism is more effective than a method [13] based on the diffusion equation.

Then, we visually confirm that the proposal mechanism can supply energies of each node according to demand amounts for each node. Figures 9(b) and 9(c) show the geographical distributions of node energies at $t = 0$ and $t = 500$ when using the node demand amounts shown in Fig. 9(a). According to these figures, the proposal mechanism has effectiveness for uniforming the geographical heterogeneity.

Moreover, we quantitatively investigate the uniforming speed of the proposal mechanism under several situations. As a metric for the uniforming speed, we use time constant, which is the time required for decreasing a initial variance $\mathrm{Var}(\hat{\boldsymbol{Q}}(0))$ to $e^{-1}\,\mathrm{Var}(\hat{\boldsymbol{Q}}(0))$.

Figure 10 shows the time constants of the proposal mechanism and the diffusion mechanism for different averages μ_q^{st} and variances $k_\sigma\,\mu_q^{\mathrm{st}}$ of initial energies. According to this figure, the proposal mechanism has higher effectiveness for both energy shortage (i.e., small μ_q^{st}) and surplus (i.e., large μ_q^{st}) situations. This phenomenon is caused by large initial variances $\mathrm{Var}(\hat{\boldsymbol{Q}}(0))$. Both energy shortage and surplus situations have a large variance $\mathrm{Var}(\hat{\boldsymbol{Q}}(0))$ at the initiation of simulation. Hence, in these situations, each node is subjected to a strong force for decreasing the variance.

Figure 11 shows time constants for different parameters κ' and diffusion coefficients k'. According to Fig. 11, the time constants for both mechanisms decrease as diffusion coefficient k' increases, and the difference between time constants of both mechanisms increases as parameter κ' increases because the force of decreasing the variance in the proposal mechanism becomes strong.

Figure 12 shows time constants for different number of nodes, N, and networks G. Note that we show the results of 4-th nearest neighbor networks because they has almost same average number of adjacent nodes as lattice grid networks. According to this figure, the time constants stay about the same value when the number of nodes increases regardless of network topology, and so the proposal mechanism also has high effectiveness in networks with a large number of nodes.

Therefore, we can confirm that the proposal mecha-

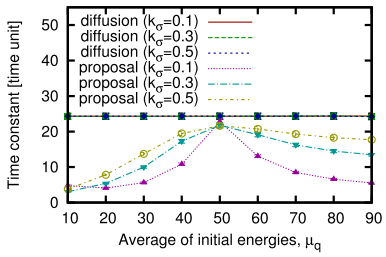


Fig. 10 Time constants for different average of initial energies, μ_q.

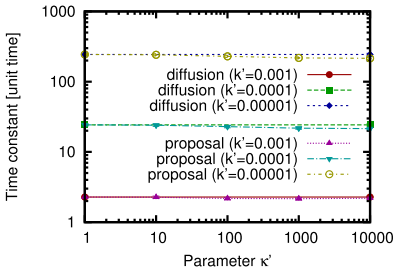


Fig. 11 Time constants for different parameter κ'.

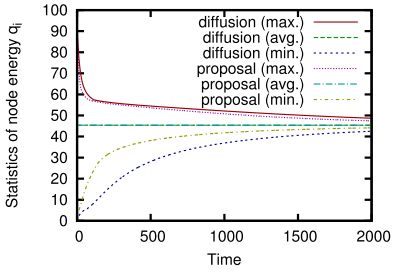


Fig. 8 Time evolution of statistics (i.e., maximum, average, and minimum) of node energies $q_i(t)$.

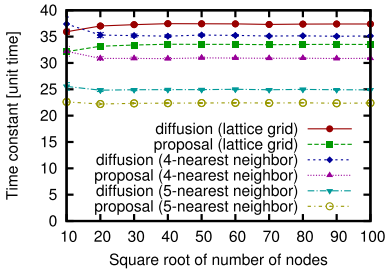
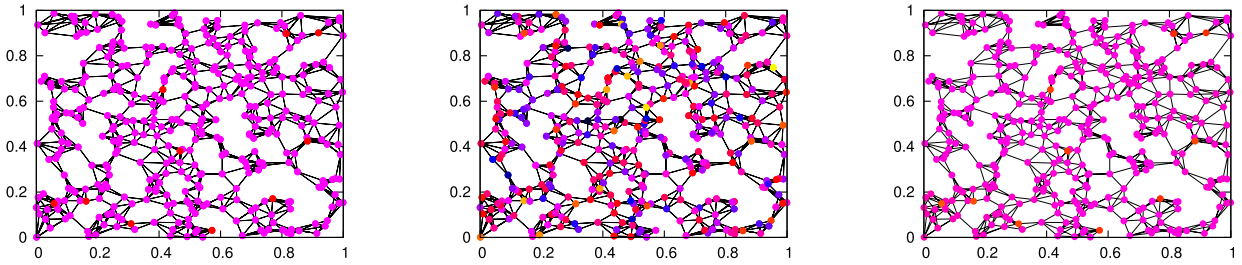


Fig. 12 Time constants for different number of nodes, N.



(a) Demand distribution (b) $t = 0$ (c) $t = 500$

Fig. 9 Geographical distributions of node energies $q_i(t)$ for heterogeneous demands.

nism has high effectiveness in several situations compared with the diffusion mechanism. However, we should also confirm the effectiveness of the proposal mechanism in a realistic situation.

5. Discussion

The uniforming of sufficiency levels by the proposed mechanism introduces the method to easily estimate the behavior of the entire system by each node. In this section, we discuss the application potentiality of this estimating method to an efficient method working with non-renewable generators while minimizing the dependence of non-renewable energy, and an incentive mechanism to prevent monopolizing energy in systems.

5.1 Supplying Energies with a Generator Using Non-renewable Energy

There is a limitation on energy supply only using renewable energy. Hence, if energy demand is higher than energy supply, a system should receive energy supply from a generator using non-renewable energy. However, for minimizing the dependence on non-renewable energy, the system must determine how much energy should be supplied from a generator using non-renewable energy. Since the proposed mechanism uniforms sufficiency levels, node i can easily estimate the shortage energy in the entire system by $N\hat{q}_i$ without gathering all information from the entire system. Figure 13 illustrates an example of supplying energy from a generator using non-renewable energy into a system based on renewable energy.

For example, during daytime, each node generates energy with PV panels, and uniforms sufficiency levels with the proposed mechanism. Then, during evening, a few nodes receives energy supply from a generator using non-renewable energy, and each node uniforms sufficiency levels again for satisfying their energy demand.

5.2 Introducing an Incentive Mechanism to Prevent Monopolizing Energy

If a few nodes maliciously set its demand amount to a very high value, the energy in a system would be monopolized by their nodes. To prevent such monopolizing energy, we discuss an incentive mechanism for decreasing the demand amount of a node.

We first introduce energy price $P(S)$ where S is the sum of sufficiency levels of all nodes. S represents the difference between energy supply and energy demand at a system level. As S increases, price $P(S)$ should increase because the energy in the system becomes shortage. Hence, as an example, we give energy price $P(S)$ by

$$P(S) = P^* - h(S), \tag{19}$$

where P^* is a basic price given by the system manager, and $h(S)$ is a cost function, which satisfies the conditions:

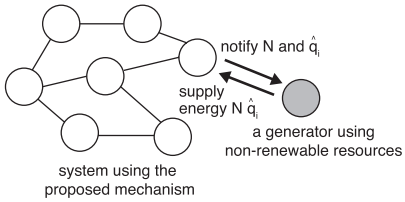


Fig. 13 An example of supplying energy from a generator using non-renewable energy.

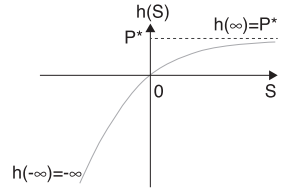


Fig. 14 Cost function $h(S)$ for energy price $P(S)$.

(a) $h(0) = 0$, (b) $h(\infty) = P^*$, and (c) $h(-\infty) = -\infty$. Under the above conditions, a cost function $h(S)$ is given by

$$h(S) = P^* \left(1 - \exp\left[-k_p S\right]\right), \tag{20}$$

where k_p is the positive control parameter for energy price $P(S)$. We illustrate cost function $h(S)$ in Fig. 14. If the system is a shortage of energy ($S < 0$), energy price $P(S)$ is high. Otherwise, energy price $P(S)$ is low. Node i can estimate S by $N\hat{q}_i$, and so it can roughly know energy price $P(S)$. Hence, energy price $P(S)$ provides an incentive for reconfiguring the demand amount of a node.

Every period (e.g., one month, one week), a management node calculates the payment for each node according to the time series of transmission power and sufficiency levels during the period. The time series are recorded by nodes, and the management node gathers them for calculating the payments of all nodes. Payment p_i of node i for period $[T_1, T_2]$ is calculated by

$$p_i = \sum_{t=T_1}^{T_2} \sum_{j \in a_i} \left\{J_{j\to i}(t) - J_{i\to j}(t)\right\} \Delta T_J \, P(S(t)). \tag{21}$$

Node i pays p_i for its energy interchanges to the management system. If $p_i < 0$, node i receives $-p_i$ from the management system. $\sum p_i = 0$ is guaranteed by the amount conservation of the diffusion equation.

Note that the management node used in the incentive mechanism is a centralized node, but is independent with the energy interchange function between nodes in the proposed mechanism.

6. Conclusion and Future Work

To realize the energy supply based on renewable energy appropriately for energy demand, this paper proposed a novel autonomous decentralized mechanism of energy interchanges based on the diffusion equation and MCMC. Since the proposed mechanism does not rely on any centralized

management systems, it has high robustness for disasters. We first derived an expression of the energy interchange amount between batteries of an adjacent node pair on the basis of the diffusion equation, and then speeded up the derived expression by using MCMC. Moreover, we visually confirmed the effectiveness of the proposed mechanism, and quantitatively investigated the uniforming speed of the proposed mechanism under several situations. Our findings establish that the proposed mechanism has high effectiveness for too energy shortage or surplus situations, and in networks with a large number of nodes.

To confirm the effectiveness of the basic ideas for the energy interchanges, this paper only performed experiments with ignorable interchange losses, and the simple setting of energy generation and consumption. Hence, as future works, we should investigate the performance of the proposed mechanism in a realistic situation with battery physical properties (e.g., the rate capacity effect and the degrading its performance), energy loss of interchanges and time variability in energy generation and consumption. Then, we will investigate the effectiveness of the method working with non-renewable generators and the incentive mechanism explained in Sect. 5. Moreover, there are other methods for accelerating the diffusion equation, so we should clarify the performance difference between the proposed mechanism and mechanisms based on the other methods.

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Yusuke Sakumoto received M.E. and Ph.D. degrees in the Information and Computer Sciences from Osaka University in 2008 and 2010, respectively. He is currently an assistant professor at Graduate School of System Design, Tokyo Metropolitan University, Japan. His research work is in the area of autonomous decentralized control for large-scale systems. He is a member of IEEE, IPSJ and IEICE.

Ittetsu Taniguchi received M.E. and Ph.D. degrees in the Information and Computer Sciences from Osaka University in 2006 and 2009, respectively. He is currently an lecturer at Graduate School of Science and Technology, Ritsumeikan University, Japan. His research interests are power saving and optimization of electrical systems, and design optimization of power systems. He is a member of IEEE and IEICE.