PAPER

# SOH aware System-level Battery Management Methodology for Decentralized Energy Network*

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**SUMMARY** The decentralized energy network is one of the promising solutions as a next-generation power grid. In this system, each house has a photovoltaic (PV) panel as a renewable energy source and a battery which is an essential component to balance between generation and demand. The common objective of the battery management on such systems is to minimize only the purchased energy from a power company, but battery degradation caused by charge/discharge cycles is also a serious problem. This paper proposes a State-of-Health (SOH) aware system-level battery management methodology for the decentralized energy network. The power distribution problem is often solved with mixed integer programming (MIP), and the proposed MIP formulation takes into account the SOH model. In order to minimize the purchased energy and reduce the battery degradation simultaneously, the optimization problem is divided into two stages: 1) the purchased energy minimization, and 2) the battery aging factor reducing, and the trade-off exploration between the purchased energy and the battery degradation is available. Experimental results show that the proposed method achieves the better trade-off and reduces the battery aging cost by 14% over the baseline method while keeping the purchased energy minimum.
***key words:*** *battery management, decentralized energy network, SOH degradation, MIP optimization*

## 1. Introduction

The large introduction of renewable energy to the power grid is a big motivation to reduce CO2 emission and to realize a sustainable future. However, renewable energy such as solar and wind is usually small scale and intermittent, and the temporal and spatial mismatch between its generation and demand is a practical issue. To tackle this problem, it is necessary to renovate the conventional power grid towards a smart energy system.

The various research regarding the smart energy system exist [1], [2]. In such systems, a decentralized energy network is one of the promising solutions [3], [4]. Each house (cluster) has a photovoltaic (PV) panel, a battery, electrical equipment, and a router to control over the system. Moreover, the clusters in a region are electrically connected, and they can transmit surplus energy to each other via the local energy network. The battery and the inter-cluster energy exchange can shift the generated energy temporally and spatially. In this way, the effective utilization of renewable energy is realized.

Recently, battery degradation is a serious problem for the smart energy systems. Li-ion batteries, the hopeful option for such grid systems, will degrade due to the operational conditions of the battery such as state-of-charge (SOC) level, charge/discharge speed, and operating temperature. Furthermore, many studies have reported that the battery degradation causes a serious capacity fading and is accelerated by aggressive battery usage [5]–[8]. Fig. 1 shows two battery usage patterns as an example. The left pattern usually has a greater effect on battery degradation than the right pattern because of aggressive battery utilization; higher average SOC and higher SOC swing. Since the battery price is very high (typically ~200 kJPY/kWh), it is important to reduce the battery degradation by managing the battery usage.

In the literature, a lot of energy management methods to control the power flow are proposed. The authors in [9] proposes a distributed battery scheduling algorithm on the smart energy system. In [10], a charge/discharge power of the battery is decided by a heuristic approach. In paper [11], a mixed-integer programming (MIP) formulation is used to manage the system operation including the battery. The objective of these papers is to minimize the total system operation cost. However, the battery degradation is not considered, and it should be taken into account in order to reduce the high battery degradation cost.

Our previous research mathematically formulates the power distribution problem as MIP with the battery charge/discharge cycle limitation [3]. The power distribution problem is a conventional problem to control the power flow on such smart energy systems. Previous research achieved the same utilization of renewable energy with quarter charge/discharge cycles of the battery, and this is expected to inhibit the battery degradation. However, the battery characteristics are complicated, and it is well known that the battery degradation is also caused by the average SOC level and the SOC swing. Furthermore, this research has not evaluated the battery degradation quantitatively.

This paper proposes a SOH aware system-level battery management methodology for the decentralized energy network. In order to evaluate and control the battery aging accurately, the SOH model is introduced to the power distribution problem. Especially, the SOC swing and the average SOC are controlled and reduced as the battery aging factors. In

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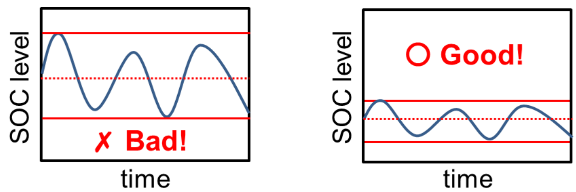


**Fig. 1** Battery usage patterns

addition, the objectives of the problem are to reduce the battery degradation and to minimize the purchased energy from a power company. However, the battery degradation and the purchased energy are essentially in a trade-off relationship, and a set point should be chosen from the trade-off based on the user preference. Therefore, the purpose of this paper is to obtain and explore the better trade-off between them rather than to realize actual system operation. Hence, the optimization problem formulated as MIP is divided into two stages: 1) the purchased energy minimization; this problem obtains the minimum purchased energy to operate the system, and 2) the battery aging factor reducing; this problem realizes the battery management to reduce its degradation with a constraint of keeping the purchased energy minimum. The effectiveness of the proposed method is demonstrated via simulations. The results show that the proposed method realizes the SOH control by aggressive battery management, and the trade-off exploitation is available.

The rest of this paper is organized as follows. Section 2 shows the decentralized energy network model. Section 3 describes the battery degradation model that we have introduced. Section 4 proposes SOH aware system-level battery management methodology. Section 5 demonstrates the simulation results and finally Section 6 concludes this paper.

## 2. Decentralized Energy Network Model

In this section, we describe the overview and the mathematical model of the decentralized energy network. Based on these descriptions, the optimization problem is formulated.

### 2.1 Overview

This section presents the decentralized energy network model. Fig.2 shows our system model. The decentralized energy network consists of $N$ clusters (houses). Each cluster is electrically connected to other clusters by the local energy network. In order to achieve the effective utilization of renewable energy, the inter-cluster energy transmission is realized by the local energy network. In case of a surplus or deficiency of the electricity, the cluster can interchange the electric energy each other.

Each cluster has a photovoltaic (PV) panel, a battery, electric equipment to consume the energy, and a router. The router is relatively common components in such smart energy systems [3], [12], [13]. The router consists of several AC/DC converters and power metering units. All devices

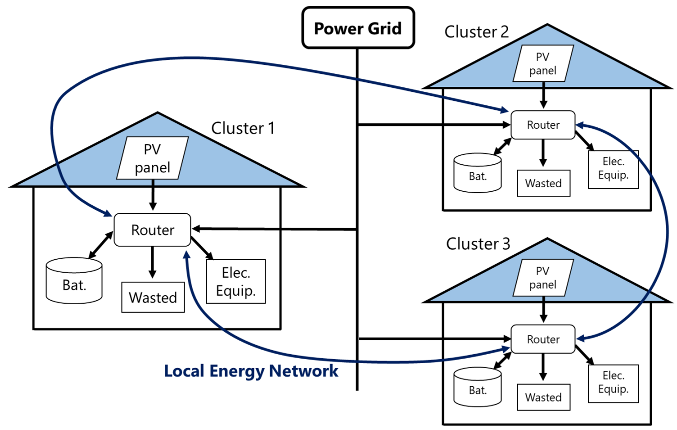


**Fig. 2** Decentralized Energy Network Model

in each cluster are connected via the router, and the clusters are connected using the router as a connection-point. The router can monitor electric power direction and energy usage. It can also control the power flow between devices and clusters by receiving the control commands from a control center. Meanwhile, the cluster can buy the electric energy from a power company via the power grid. Contrarily, the decentralized energy network does not support selling the surplus energy to the power company. The surplus energy is stored to a battery, transmitted to other clusters, or wasted in the cluster. Then, we introduce the concept of wasted energy into each cluster in order to consume the surplus energy by oneself and to prevent reverse power flow to the power grid.

The problem is how to decide how much energy is sent to which devices or clusters. We call it *power distribution problem*. The power distribution problem is usually solved by mathematical optimization. The previous research calculates the optimal power distribution to minimize the purchased energy [3]. Minimizing the purchased energy realizes the effective utilization of renewable energy, and the potential performance of the decentralized energy network is extracted. Meanwhile, a battery is an essential component in this system, and battery degradation is a serious problem because of its high price. Thus, we consider the battery degradation control in the power distribution problem.

### 2.2 Mathematical model

This section describes the fundamental MIP formulation for the power distribution problem. Let $i$, $t$, and $u$ be cluster number, day, and time respectively. Their ranges are as follows: $1 \leq i \leq N$, $1 \leq t \leq T$, and $1 \leq u \leq U$. In addition, the inputs, the decision and dependent variables, and the parameters used in the proposed formulation are described, respectively, in Tables 1-3. Here, let $j$ be also cluster number to formulate the inter-cluster energy exchange, and its range is $1 \leq j \leq N, i \neq j$. The units of value which are not mentioned in the tables are kWh. Note that we assume all inputs are perfectly predicted before formulation, and we use the measured value.

The battery behavior is not ideal, and some electrical energy is lost when charging the battery. The stored energy at the next time $u+1$ and the SOC level at time $u$ of the battery is calculated by Eq. (1) and (2), respectively. Note that the SOC level means the ratio of the available energy to the battery capacity.

$$X_{i,t,u+1} = X_{i,t,u} + \alpha_i B^{in}_{i,t,u} - B^{out}_{i,t,u}, \quad \forall i, \forall t, 1 < u \leq U \tag{1}$$

$$SOC_{i,t,u} = \frac{X_{i,t,u}}{\overline{X_i}}, \quad \forall i, \forall t, \forall u \tag{2}$$

In order to avoid over-charge/discharge and use a battery safely, the battery capacity and maximum charge/discharge speed given by a manufacturer should be taken into account.

$$\underline{X_i} \leq X_{i,t,u} \leq \overline{X_i}, \quad \forall i, \forall t, \forall u \tag{3}$$

$$0 \leq B^{in}_{i,t,u} \leq XC_i, \quad \forall i, \forall t, \forall u \tag{4}$$

$$0 \leq B^{out}_{i,t,u} \leq XC_i, \quad \forall i, \forall t, \forall u \tag{5}$$

Eq. (3) guarantees the battery should not exceed the minimum and maximum capacity. Eq. (4) and (5) are the constraints on charge and discharge speed for each time $u$.

Additionally, the following equations for the battery are simultaneously satisfied.

$$X_{i,1,1} = X^0_i, \quad \forall i \tag{6}$$

$$X_{i,T,U+1} = X^0_i, \quad \forall i \tag{7}$$

$$X_{i,t+1,1} = X_{i,t,U+1}, \quad \forall i, 0 \leq t < T \tag{8}$$

Eq. (6) set the initial stored energy of the battery at the beginning of planning period. Eq. (7) define that the end value of the stored energy is the same as initial energy $X^0_i$. At the end of each day, Eq. (8) take over the stored energy to the next day $t+1$.

The inter-cluster energy exchange between clusters is realized by the local energy network which consists of private electric cables. Such local energy network usually has the upper bound of transmitted energy, and energy loss occurs during energy exchange due to the cable resistance. The energy exchange by local energy network is described by the following equations:

$$0 \leq Z_{i,j,t,u} \leq \gamma_{i,j}, \quad \forall i, \forall j, \forall t, \forall u, i \neq j \tag{9}$$

$$Z^T_{i,t,u} = \sum_{j=1, j\neq i}^{N} Z_{i,j,t,u}, \quad \forall i, \forall t, \forall u \tag{10}$$

$$Z^R_{i,t,u} = \sum_{j=1, j\neq i}^{N} \beta_{j,i} Z_{j,i,t,u}, \quad \forall i, \forall t, \forall u \tag{11}$$

Eq. (9) is the constraint of the transmission capacity between the cluster $i$ and $j$. Eq. (10) calculates the transmitted energy from the cluster $i$. Eq. (11) obtains the received energy from the other clusters to the cluster $i$ with the energy exchange loss.

**Table 1** Inputs

| Inputs | Description |
|---|---|
| $D_{i,t,u}$ | Electric demand of cluster $i$ at day $t$, time $u$ |
| $G_{i,t,u}$ | Generation energy from PV panel of cluster $i$ at day $t$, time $u$ |

**Table 2** Decision and dependent variables

| Variables | Description |
|---|---|
| $S_{i,t,u}$ | Purchased energy from utility grid of cluster $i$ at day $t$, time $u$ |
| $Y_{i,t,u}$ | Wasted energy of cluster $i$ at day $t$, time $u$ |
| $X_{i,t,u}$ | Battery stored energy of cluster $i$ at day $t$, time $u$ |
| $B^{in}_{i,t,u}$ | Charged energy to cluster $i$'s battery at day $t$, time $u$ |
| $B^{out}_{i,t,u}$ | Discharged energy from cluster $i$'s battery at day $t$, time $u$ |
| $Z_{i,j,t,u}$ | Transmission energy from cluster $i$ to cluster $j$ at day $t$, time $u$ |
| $SOC_{i,t,u}$ | SOC level of cluster $i$'s battery at day $t$, time $u$ [%] |
| $Z^T_{i,t,u}$ | Transmitted energy from cluster $i$ to the other clusters at day $t$, time $u$ |
| $Z^R_{i,t,u}$ | Received energy of cluster $i$ from the other clusters at day $t$, time $u$ |

**Table 3** Parameters

| Parameters | Description |
|---|---|
| $X^0_i$ | Initial stored energy of the cluster $i$'s battery |
| $\underline{X_i}$ | Lower bound for the stored energy of the cluster $i$'s battery |
| $\overline{X_i}$ | Upper bound for the stored energy of the cluster $i$'s battery |
| $XC_i$ | Charge/discharge speed for the cluster $i$'s battery |
| $\alpha_i$ | Charging efficiency of the cluster $i$'s battery [%] |
| $\beta_{i,j}$ | Attenuation rate of the energy exchange between cluster $i$ and cluster $j$ [%] |
| $\gamma_{i,j}$ | Capacity for the energy exchange between cluster $i$ and cluster $j$ |

Regarding the power distribution by a router, the following equations must be satisfied.

$$S_{i,t,u} \geq 0, \quad \forall i, \forall t, \forall u \tag{12}$$

$$Y_{i,t,u} \geq 0, \quad \forall i, \forall t, \forall u \tag{13}$$

$$\begin{aligned} & S_{i,t,u} + G_{i,t,u} + B^{out}_{i,t,u} + Z^R_{i,t,u} \\ & = Y_{i,t,u} + D_{i,t,u} + B^{in}_{i,t,u} + Z^T_{i,t,u}, \quad \forall i, \forall t, \forall u \end{aligned} \tag{14}$$

Eq. (12) presents the cluster can only buy the electrical energy from the power company. Eq. (13) means the wasted energy must take the positive value. Eq. (14) is the router equations that the sum of the incoming energy equals the sum of the outgoing energy on the router.

## 3. Battery Degradation Model

This section introduces the Millner's SOH model as the battery degradation model [14]. In this model, the battery aging is defined by the SOH based on battery capacity loss. The SOH is the ratio of the present battery capacity to the initial its capacity, and it is defined as follows:

$$SOH^m = \frac{X^m_{full}}{X^0_{full}}, \tag{15}$$

where $SOH^m$ and $X^m_{full}$ are the SOH and the actual capacity after $m$ charge/discharge cycles, respectively. $X^0_{full}$ is the nominal capacity of the battery. Thus, the SOH of the new battery is 1.0 (100%), and the battery degradation is expressed by the SOH decrease. When the SOH reaches 80%, the battery is usually assumed to be useless due to serious capacity fading and an increase of internal resistance of the battery.

The SOH estimation is a difficult task because the SOH degradation is caused by complex electrochemical reactions inside the battery. Some electrochemical-based SOH models proposed in [15], [16] are quite accurate based on physical phenomena. In addition, data-driven approaches proposed in [17], [18] can predict battery lifetime fairly good without a full understanding of the mechanism. However, these models are not suitable for a MIP formulation because they consist of complex nonlinear equations and are too complicated to solve by MIP. In this paper, we use the Millner's model that can calculate the SOH degradation during the charge/discharge cycle based on the battery's SOC trace [14]. This model also consists of non-linear equations, but it is not too complex and can be applied to MIP using linear-approximation technique. In addition, this model shows good agreement with the experimental data. Thus, it can be applied to our optimization problem.

Now we introduce the SOH model proposed by Millner. Firstly, the SOC is defined by:

$$SOC = \frac{X_{str}}{X^m_{full}}, \tag{16}$$

where $X_{str}$ is the stored energy in the battery. The variable $SOC_{avg}$ represents the average SOC over a cycle, and $SOC_{swing}$ is the SOC swing which means the ranges between the maximum and the minimum SOC level in a cycle. Finally, the SOH degradation in the $m$-th charge/discharge cycle, denoted by $L_{cycle,m}$, is calculated as follows:

$$L_{cycle,m} = L_2 \cdot \exp\left[K_T\left(T_B - T_{ref}\right)\frac{T_{ref}+273}{T_B+273}\right], \tag{17}$$

$$L_2 = L_1 \cdot \exp\left[4K_{SOC}\left(SOC_{avg} - 0.5\right)\right] \cdot SOH^m, \tag{18}$$

$$L_1 = K_{CO}\cdot\exp\left[\left(SOC_{swing} - 1\right)\frac{(T_{ref}+273)}{K_{EX}(T_B+273)}\right] + 0.2\frac{\tau}{\tau_{life}}, \tag{19}$$

where $K_T$, $K_{SOC}$, $K_{CO}$, and $K_{EX}$ are the battery specific parameters. $T_B$ and $T_{ref}$ are battery temperature and reference temperature, respectively. $\tau$ is the time in seconds of $m$-th charging/discharging cycle, and $\tau_{life}$ is the total expected calendar life in seconds. In this paper, we use the value of these parameters given in the literature.

Millner reported that the higher average SOC and the higher SOC swing accelerate the SOH degradation [14]. This result is not limited in Millner's SOH model, and many studies have reported that they are the main battery aging factors [5]–[8]. Thus, we formulate the power distribution to control both the average SOC and the SOC swing in order to reduce the battery degradation.

## 4. SOH aware System-level Battery Management

This section proposes the SOH aware battery management method as the MIP formulation. In order to reduce the SOH degradation, the direct introduction of the SOH degradation model into the optimization problem is the most effective approach. However, the SOH model is non-linear, and such a non-linear optimization problem cannot be solved in the practical time. Therefore, we try to reduce the SOH degradation indirectly by controlling the battery aging factors. As described in Section 3, a higher SOH degradation rate is caused by both a higher SOC swing and a higher average SOC, and we treat them as the battery aging factors. Because our purpose is to obtain and explore the trade-off between the purchased energy and the battery degradation, we need to calculate various set points of the amount of the purchased energy and minimum battery aging cost which correspond to that. To achieve this, we especially focus on the SOC swing that affects both of the purchased energy and the battery degradation. Firstly, a large SOC swing clearly reduces the purchased energy while the battery is more deteriorated. On the contrary, a small SOC swing apparently reduces the battery degradation while the purchased energy increases. Thus, we can explore the optimal solution in the trade-off by introducing a constraint for the SOC swing to keep it below an upper-bound. The advantage of this approach is easy to explore the trade-off by adjusting only the upper-bound of the SOC swing. In contrast, we also focus on the average SOC which have a relative small impact for the purchased energy as other battery aging factor. We propose to minimize the degradation effect of the average SOC as an objective function in order to obtain the better trade-off. Then, we derive the objective function from the SOH model by Millner. In short, our approach is to introduce the following formulation: 1) a constraint for SOC swing control and 2) a penalty function of average SOC based on the SOH model, which are described in Section 4.1 and Section 4.2, respectively. In addition, we describe the details of the proposed battery management formulation in Section 4.3.

### 4.1 Constraint for SOC swing control

We present the constraints for SOC swing control. Firstly, the SOC swing in the MIP formulation, denoted by $SOC^{swing}_{i,t}$, is given as follows.

$$SOC^{swing}_{i,t} = \max_{1\le u\le U} SOC_{i,t,u} - \min_{1\le u\le U} SOC_{i,t,u}, \quad \forall i, \forall t \tag{20}$$

For a simplification, we define $SOC_{i,t}^{swing}$ as the ranges between the maximum and the minimum SOC level of cluster $i$ at the day $t$. Note that several binary (integer) variables are internally introduced in the formulation in order to express Eq. (20).

In order to limit $SOC_{i,t}^{swing}$ and control the battery usage, we introduce the following constraint:

$$0 \leq SOC_{i,t}^{swing} \leq SWING_{max}, \quad \forall i, \forall t \tag{21}$$

where $SWING_{max}$ is the upper bound of SOC swing for a day, of which the range can take over from 0 to 1. If the value of $SWING_{max}$ is small, the SOC swing is strictly restricted, and the $SWING_{max}$ of 0 means that the battery cannot be used because of the constraint. As discussed in Section 4, we can easily explore the trade-off between the battery degradation and the purchased energy by adjusting only one parameter $SWING_{max}$.

### 4.2 Penalty function of average SOC

The average SOC is a significant portion of the battery aging factor. Because the average SOC have a relative small impact for the purchased energy, we propose to minimize the battery damage caused by the average SOC to reduce the battery degradation. As shown in Eq. (18) of the SOH model, the battery damage is an exponential function of the average SOC. We assume that minimizing Eq. (18) is more effective to reduce the battery degradation than simply minimizing the sum of the average SOC. Hence, we introduce a penalty function based on Eq. (18) and minimize it as an objective function. At first, the average SOC in the MIP formulation, denoted by $SOC_{i,t}^{avg}$, is defined as follows.

$$SOC_{i,t}^{avg} = \sum_{u=1}^{U} \frac{SOC_{i,t,u}}{U}, \quad \forall i \forall t \tag{22}$$

Originally, the average SOC is the average level for each charge/discharge cycle. However, we simplify it as the average SOC of cluster $i$ at the day $t$ in order to save computational time.

The penalty function of the average SOC is defined based on Eq. (18) of the SOH model as follows:

$$P(x) = \exp\left[4K_{SOC}(x - 0.5)\right], \tag{23}$$

where $x$ means the average SOC which takes from 0 to 1.0, and this function represents the battery damage affected by the average SOC. Since $P(x)$ is an exponential function, it is cannot be introduced into MIP formulation. Thus, we linearize this non-linear function using piecewise-linear approximation technique. Let $n$ be a number of sampling coordinates $x_1, \ldots, x_n$. Here, $x_1$ and $x_n$ correspond to the average SOC of 0 and 1.0, respectively. Then, the function is approximated by a set of linear lines for each intervals $[(x_k, P(x_k)), (x_{k+1}, P(x_{k+1}))](k = 1, \ldots n-1)$. We define this set of linear lines as approximated penalty function $\tilde{P}(x)$. In order to minimize the battery damage affected by the average SOC, we set the sum of $\tilde{P}\left(SOC_{i,t}^{avg}\right)$ as an objective function in the optimization problem. Note that several binary variables are internally introduced in the formulation to express the equation $\tilde{P}\left(SOC_{i,t}^{avg}\right)$. Our formulation is MIP owing to Eq. (20) and this piecewise-linear function.

### 4.3 SOH aware battery management optimization

We describe the proposed SOH aware battery management formulation based on the power distribution problem. As mentioned above, there are two objectives for this problem: 1) minimizing the purchased energy from the power company and 2) reducing the battery's SOH degradation. In order to achieve them and obtain the trade-off of them, we propose dividing the optimization problem into two-stage:

- Stage 1: the purchased energy minimization.
- Stage 2: the battery aging factor reducing.

The first stage calculate the minimum purchased energy to operate the system, and the second stage calculates battery scheduling to reduce its aging factors under a constraint of the minimum purchased energy. The constraint for the SOC swing is introduced into both stages to explore the trade-off, and the penalty function of the average SOC is set to the objective function in stage 2 to reduce the battery degradation.

We can employ an one-stage optimization where a weighted sum of the purchased energy and the penalty function is set to the objective function. However, it is difficult to find out the optimal weight parameters in the one-stage optimization. This is because the optimal weight always changes with the purchased energy, of which the amount depends on the situation such as season and weather. On the contrarily, the two-stage structure is no need for searching the optimal weight and easily explore the trade-off. In this respect, the two-stage structure is more suitable for our purpose. The details of the proposed formulation are described as following sections.

#### 4.3.1 Stage 1: Purchased energy minimization

In the stage 1, we calculate the minimum purchased energy to operate the system by solving the following optimization problem:

$$\begin{aligned} &\text{minimize} && S_{total} = \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{u=1}^{U} S_{i,t,u}, \qquad (24) \\ &\text{subject to} && (1) - (14), (20), (21), \\ &\text{decision variables :} && \\ & && S_{i,t,u}, Y_{i,t,u}, X_{i,t,u}, B_{i,t,u}^{in}, B_{i,t,u}^{out}, Z_{i,j,t,u}, \\ & && \forall i, \forall j, \forall t, \forall u, i \neq j, \end{aligned}$$

where this problem includes the constraints for SOC swing and the upper bound $SWING_{max}$ as a parameter. The objective function (24) is to minimize the sum of the purchased energy of all clusters for the planning period. The obtained minimum purchased energy, denoted by $S^*_{total}$, is used to interpolate between the optimization problems of each stage and to keep the purchased energy minimum. With different settings of $SWING_{max}$, $S^*_{total}$ takes a different value. In the stage 1, we also obtain the schedules of the system operation for each cluster at each time slot. However, these schedules are discarded and then recalculated in the stage 2 to consider the battery aging factor.

### 4.3.2 Stage 2: Battery aging factor reducing

In the stage 2, the following optimization problem is solved to calculate the final outputs, i.e., the optimal schedules to achieve two objectives mentioned above:

$$\text{minimize} \qquad Damage = \sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{P}\left(SOC^{avg}_{i,t}\right), \quad (25)$$

$$\text{subject to} \qquad (1)-(14), (20)-(22),\ (24),$$

$$S_{total} \le S^*_{total}, \quad (26)$$

decision variables :

$$S_{i,t,u}, Y_{i,t,u}, X_{i,t,u}, B^{in}_{i,t,u}, B^{out}_{i,t,u}, Z_{i,j,t,u},$$
$$\forall i, \forall j, \forall t, \forall u, i \neq j,$$

where this also includes the constraint for SOC swing. The objective (25) is to minimize the linearized penalty function described in Section 4.2. In addition, Eq. (26) is a constraint for the purchased energy. Note that $S^*_{total}$ is the minimum value of the purchased energy obtained by the stage 1. Therefore, the constraint (26) allows the system to utilize only the necessary purchased energy, and the total purchased energy is also kept at a minimum in the stage 2. Finally, the output of the proposed method is the optimal schedules for the energy purchase, the battery usage, the energy transmission, and the wasted energy. The proposed method considers minimizing the purchased energy and reducing the battery aging factor at the same time.

## 5. Experimental Results

In this paper, we perform the optimization and simulation with practical assumptions. Firstly, we introduce two criteria for evaluating the effectiveness of the proposed method: 1) the battery aging cost and 2) the total system cost. The battery aging cost based on the SOH, denoted by $COST_{aging}$ is given by:

$$COST_{aging} = \sum_{i=1}^{N}\frac{1-SOH_i}{1-SOH_{lim}}COST_{bat}, \quad (27)$$

where $SOH_i$ is the SOH of the cluster $i$'s battery after a one-year operation. $SOH_{lim}$ is a threshold of the SOH to indicate the battery's end-of-life, and $COST_{bat}$ is a cost to replace the battery when reaching its end-of-life. We assume that $SOH_{lim} = 0.8$, and $COST_{bat} = 200$ kJPY/kWh. In addition, the total system cost, denoted by $COST_{year}$, is calculated by:

$$COST_{year} = COST_{aging} + S^*_{total}\cdot COST_{grid}, \quad (28)$$

where $COST_{grid}$ is the electricity price per one unit of energy (kWh) in the power grid. We assume the electricity price is a constant regardless of time and purchase peak power, then $COST_{grid}$ is set to 21 JPY/kWh.

**Table 4** Parameter settings

| Parameter | Value | |
|---|---|---|
| Upper bound of the stored energy in the battery | $\overline{X_i} = 3$ | $\forall i$ |
| Lower bound of the stored energy in the battery | $\underline{X_i} = 0.3$ | $\forall i$ |
| Initial stored energy in the battery | $X^0_i = 0.3$ | $\forall i$ |
| Charge/discharge speed of the battery | $XC_i = 3$ | $\forall i$ |
| Charging efficiency of the battery | $\alpha_i = 0.9$ | $\forall i$ |
| Attenuation rate of the energy exchange | $\beta_{i,j} = 0.95$ | $\forall i, \forall j; i \neq j$ |
| Capacity of the energy exchange | $\gamma_{i,j} = 100$ | $\forall i, \forall j; i \neq j$ |

The other setting of the experiment is described below. For the decentralized energy network, we consider five clusters ($N = 5$), and the clusters are completely connected by local energy network. The planning period is one month ($T = 31$), and the hourly power distribution is calculated by optimization ($U = 24$). The inputs are the real PV generation and demand profiles measured at five different houses in Shiga, Japan. Thus, the inputs are all different between 5 clusters. The MIP solver is IBM ILOG CPLEX v.12.7 [19]. We use the parameters of the SOH model presented in the literature [14]. The other parameters of the optimization problem are shown in Table 4.

The proposed method (marked as *Proposed*) is compared with the baseline method (marked as *Baseline*). The baseline method employs only stage 1 optimization, i.e., the objective is to minimize only the purchased energy with the SOC swing constraint. Then, we perform the experiment as following steps:

1. Following optimization is calculated for each month, and the battery charge/discharge trace for a whole year is obtained.
    a. Stage 1: Purchased energy minimization with $SOC^{swing}_{i,t}$ constraint (21) changing the upper bound $SWING_{max}$ from 0.1 to 0.9.
    b. Stage 2: Minimization of the penalty function (25) with $SOC^{swing}_{i,t}$ constraint (21) and corresponding minimized purchased energy constraint (26).
2. SOH degradation is calculated with the battery charge/discharge trace obtained by the above optimization based on the SOH model.
3. Battery aging cost and total system cost is derived by Eq. (27) and (28), respectively.

Firstly, to investigate the effect of the SOC swing constraint (21) on the minimum purchased energy, we simulate the baseline and proposed method changing the upper bound $SWING_{max}$ from 0.1 to 0.9. The results of the purchased energy is shown in Fig.3. The minimum purchased energy

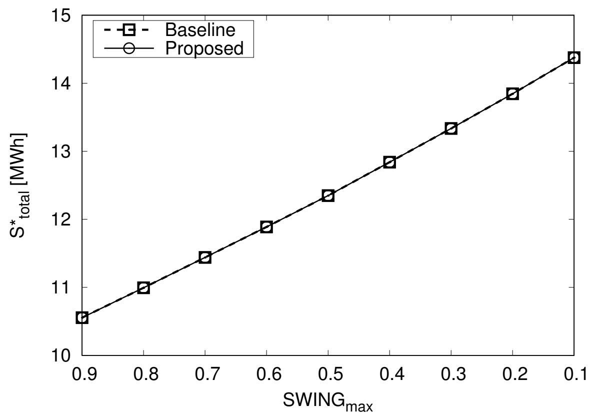


**Fig. 3** Relationship between the sum of purchased energy and the upper bound of the SOC swing

$S^*_{total}$ increases as $SWING_{max}$ is set to smaller value. This is because the limitation of the battery causes the mismatch between renewable energy and demand. Besides, for each $SWING_{max}$ settings, the minimum purchased energy of the proposed and that of the baseline are the same due to the purchased energy constraint (26).

Fig.4 shows the optimized battery SOC trace for typical 4 days when the baseline and proposed method employed that $SWING_{max}$ is 0.4 or 0.9. Comparing $SWING_{max} = 0.9$ with $SWING_{max} = 0.4$, the ranges of the SOC are limited and controlled. On the other hand, the proposed method consistently achieves lower SOC traces compared with the baseline method. It appears that minimization of the penalty function (25) results in reducing the average SOC.

We also demonstrate the impact on the battery aging cost by considering the battery aging factors. Fig.5 shows the trade-off between the sum of the purchased energy and the battery aging cost. Dotted line and solid line correspond to the proposed method and the baseline method, respectively. The result shows that the proposed method obtains the better trade-off over the baseline one, and the battery aging cost can be reduced up to 14% under the same purchased energy.

We finally calculate the total system cost for the one-year operation. In Fig.6, the total system cost to operate one year by the proposed method is shown. As we can see, when $SWING_{max}$ is set to 0.6, the total system cost is minimum. This is because the increase of the electricity cost exceeds the decrease of the battery aging cost bordering $SWING_{max} = 0.6$. In this case study, the optimal settings of the upper bound $SWINGmax$ is assumed to be 0.6 from the viewpoint of the total system cost.

## 6. Conclusion and Future Work

This paper proposes a SOH aware system-level battery management methodology for the decentralized energy network. The decentralized energy network is a next-generation grid system toward independence from a conventional power grid. The purpose of this paper was to obtain and explore the trade-off relationship between the purchased energy and the battery degradation. Specifically, we formulate the power distribution problem on this system as a MIP in order to minimize the purchased energy and reduce battery degradation simultaneously. The battery SOH model is introduced to this problem, and the battery aging factors are taken into account. The proposed method consists of two stage optimization problems: 1) purchased energy minimization, and 2) reducing battery degradation. Experimental results show that the proposed method reduces the battery aging cost by 14% over the baseline method, of which the objective is to minimize only the purchased energy, and the better trade-off between the battery degradation and the purchased energy is available.

We have some directions for future work. Our method is based on the assumption that the amount of future renewable generation is already-known. However, in actual operation, the amount of renewable energy is unknown and changes with weather condition. It is necessary to deal with this uncertainty to renewable energy. Therefore, one direction for future work is to develop a real-time optimization framework with the forecast information such as power demand and renewable generation. In particular, integrating of PV forecasting model such as [20] is a promising solution to increase the robustness to the uncertainty of renewable energy. On the other hand, there are many approaches to reduce the battery degradation and the purchased energy, e.g. considering cycle number as a battery parameter and employing one-stage optimization. We will evaluate these approaches and design an optimal methodology. We are also interested in extending a battery model to consider charge/discharge loss accurately, e.g., an equivalent circuit model of the battery [21] will be integrated into the framework.

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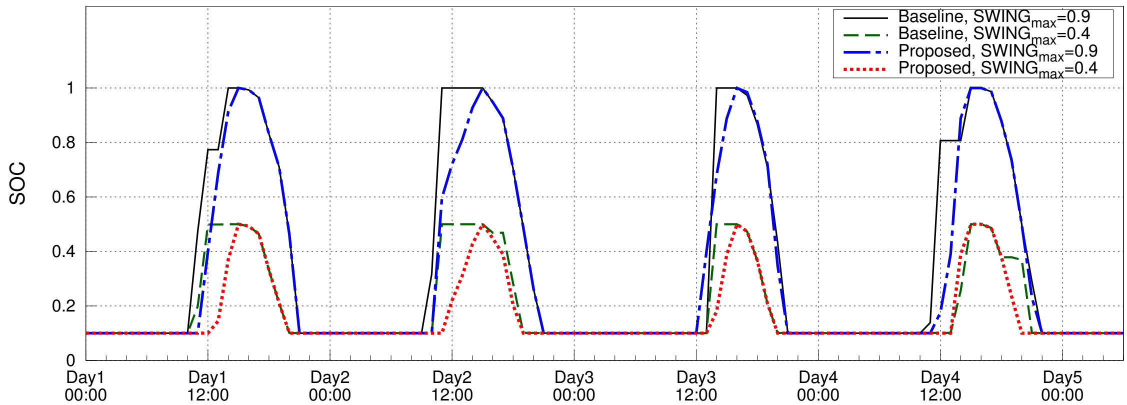


**Fig. 4** Batter SOC trace of Baseline and Proposed of cluster 1 for days in autumn with different $SWING_{max}$

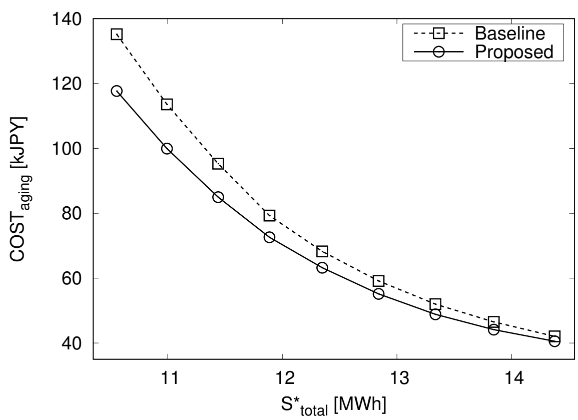


**Fig. 5** Tradeoff between the sum of purchased energy and the battery aging cost

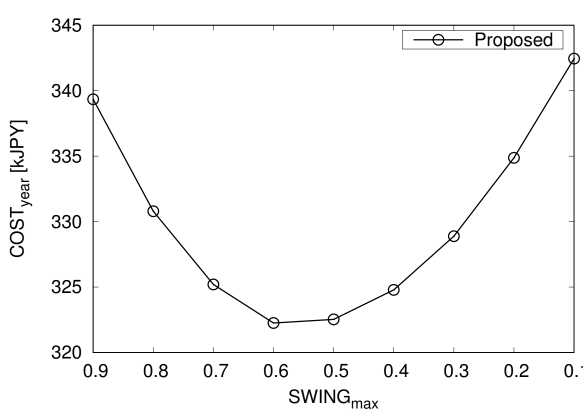


**Fig. 6** Total system cost of the proposed method with different upper bounds of the SOC swing

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