1. Introduction

Smart grids operate high-quality energy management with information and communication technology [1]. The smart grids have control systems called Energy Management Systems (EMS) for balancing of demand and supply of electricity. There are several EMSs depending on each purpose, for example, Home Energy Management System (HEMS) is for an ordinary home. The EMSs require electricity storages as buffers to be more robust from highly fluctuation in demand and supply of electricity [2]. The energy storages are especially required for renewable energy such as solar power [3],[4] or wind power [5].

However, the installing cost of the high capacity energy storage is very expensive, therefore, an alternative device is necessary. Then, the authors have focused on in-vehicle batteries installed in Electric Vehicles (EVs) or Plug-in Hybrid Vehicles (PHVs) which are utilized as electricity storages in power grid since these batteries also have high capacity. Such a system using in-vehicle battery is called Vehicle-to-Grid (V2G) or Vehicle-to-Home (V2H). In the V2G, massive in-vehicle batteries are utilized to balance demand and supply in a grid connecting large scale renewable energy farms [6]–[8]. Since the charging power of the massive in-vehicle batteries will impact on the grid, the charging schedules should be managed [9]. In contrast with the V2G, the V2H is for small scale balancing in a house with some energy devices such as Photovoltaic (PV) where the in-vehicle battery works to adjust purchase or selling power which depends on human activity for each time. For example, when a vehicle is away from a house, the in-vehicle battery cannot be use for the house. Therefore, the charge/discharge scheduling is the most important to utilize the in-vehicle batteries.

Then, the authors have proposed a HEMS with V2H system considering vehicle use shown in Fig. 1, which achieved to reduce electricity fee of houses only by charge/discharge scheduling of in-vehicle battery without the reduction of the total electricity consumption [10].

On the other hand, recently in Japan, EMSs will become popular not only with ordinary homes but also with apartment buildings because of three factors. First, a feed-in-tariff of electricity generated by PV systems has been enacted. Ordinary homes are permitted to payback for surplus electricity sent to the power grid, and power industry can sell the full amount of electricity generated by PV units in accordance with a full amount purchase system for renewable energy. Thus, the number of PV systems will be increasing in future. Second, as a model of business, some apartment buildings are installed a system that distributes power collectively received at high voltage to consumers such as general households. This system can reduce operating costs by using existing equipment and facilities while reducing contracted power. Third, a subsidy system for companies that provide Mansion Energy Management Systems (MEMS) is written as BEMS in conformity with English expression.
tems (MEMS) has been enforced as a policy of Agency for Natural Resources and Energy, Ministry of Economy, Trade and Industry. By such factors, the authors consider that design, development and improvement of BEMS for apartment buildings have been highly required. However, existing studies of BEMS only for office buildings which manages air conditioning, lighting and power for devices such as elevators.

Hence, the authors propose a BEMS for apartment buildings by extension of the HEMS with V2H. The BEMS, where plural EVs or PHVs are expected to be connected to the system, optimizes and operates the charging/discharging schedule of in-vehicle batteries in group optimization based on model-predictive control (MPC), and realizes effective energy management in the target building. A special property is electricity interchange by discharging of in-vehicle batteries to households in the same building. Through computational experiments, the authors verify the usefulness of our proposed BEMS with the electricity interchange.

The remaining part of this paper is organized as follows. Section 2 explains the model-predictive HEMS using the in-vehicle battery. In Section 3, model-predictive BEMS for apartment buildings is proposed as an extension of the HEMS. The usefulness and effectiveness of the proposed BEMS are verified and discussed in Section 4, and the authors conclude this paper with future work in Section 5.

2. Model Predictive HEMS

The HEMS [10] controls only electricity power of charge or discharge of in-vehicle batteries without adjusting or shifting basic electricity consumption in home. The HEMS has three important properties as follows:

- Vehicle-to-Home (V2H) System,
- charge/discharging scheduling of in-vehicle battery and
- Model-predictive Control (MPC).

The Vehicle-to-Home (V2H) systems operate in-vehicle batteries installed in EVs/PHVs in the same way as an stationary battery in a home based on a DC power network [11]. However, these batteries can not use in all time as electricity power sources for home because the EVs/PHVs are usually used as automobiles. Therefore, the HEMS needs a prediction method to obtain future profiles of vehicle use whether an EV/PHV is at home or not. To resolve this problem, the authors have also proposed a prediction method for vehicle use and confirmed this usefulness [12].

For each time, the charge/discharging scheduling of the in-vehicle batteries is optimized to minimize electricity cost for coming 24 hours based on model-predictive control [13]. In this optimization, the HEMS needs information of electricity consumption and generation by a PV unit for coming 24 hours, otherwise, the HEMS cannot decide to charge or discharge and its electricity because it is unknown when the efficasy of charging/discharging is the highest. Then, not only for vehicle use but also for electricity consumption and generation, prediction methods are required in order to operate the HEMS.

Therefore, the Model-predictive control (MPC) should be applied to the charge/discharging scheduling of the in-vehicle batteries, because the MPC process can respond the variation of electricity consumption and electricity generation in progress of time [5],[8],[14],[15]. With this reason, the authors have applied the MPC process to the HEMS with V2H system.

2.1 Control Procedure Based on MPC

The control procedure of the HEMS based on model predictive control is depicted in Fig. 2 and described as follows:

1) Observe information of sensors attached to the home, and predict profiles of electricity consumption, generation and vehicle use for coming T steps at current time t.

2) Optimize the charge/discharging schedule of in-vehicle batteries to minimize electricity fee with the predicted result for coming T steps.

3) Operate the charge/discharging schedule only for Δt as a control period and return to 1), then, the current step is finished.

2.2 Formulation

In this section, the charge/discharging scheduling is formulated as an optimization problem categorized in Mixed Integer Liner Problem (MILP). First, variables and parameters for the formulation are listed. Consequently, the formulation is described with Mixed Logical Dynamical System (MLDS). Finally, the authors show a result in computational experiment of the model-predictive HEMS.

2.2.1 Variables and parameters

We assume that a home has a PV device set and one or several EVs or PHVs. Definitions of decision variables in the HEMS are described below.

\[ p_h^d(k) \] : Charging/Discharging power of vehicle j of home h at time k (kW).

And definitions of parameters in the HEMS are shown in the following.

\[ \tilde{W}_h^c(k) \geq 0 \] : Electricity consumption of home h in time period at t (kW).

\[ \tilde{W}_h^g(k) < 0 \] : Electricity generation of home h in time period at t (kW).

\[ f_h^c(t) > 0 \] : Purchase price of electricity at t (JPY/kWh).

\[ f_h^s(t) > 0 \] : Sale price of electricity at t (JPY/kWh).

\[ \tilde{y}_h^c(k) \in [0,1] \] : Binary variable wherein vehicle j of home h is connected to HEMS or not.
Fig. 3 Profile of $\tilde{\gamma}_j(k|t)$ over 24 hours from the present time $t$.

$\tilde{\gamma}_j(k|t)$ is represented as traveling state, a binary variable wherein the vehicle is available or not as a power storage in the HEMS. When the vehicle is available, $\tilde{\gamma}_j(k|t)$ is 0. Figure 3 depicts an example of a profile of $\tilde{\gamma}_j(k|t)$ over 24 hours. $p_{h,j}^{\text{char}}(k)$ describes charge/discharge electric power in the V2H system. When $p_{h,j}^{\text{char}}(k)$ has a positive value, the in-vehicle battery $j$ is charging. Similarly, when the value is negative, the battery is discharging. In this paper, let $\tilde{W}_h^s(k|t)$, $\tilde{W}_h^p(k|t)$ and $\tilde{\gamma}_j(k|t)$ be already-known values.

2.2.2 Optimization problem of charge/discharge scheduling

For charge/discharge scheduling of the in-vehicle batteries, we formulate the optimization problem in the model predictive control as Mixed Integer Linear Programming (MILP). Let the present time be $t$, given parameters, decision variables, constraints and the objective function are shown in the following.

**Given:**

$\{W_h^s(k|t), W_h^p(k|t), f_h^s(k), f_h^p(k), \tilde{\gamma}_j(k|t), B_{h,j}^{\text{cons}}(k|t), B_{h,j}^{\text{init}}(k|t), B_{h,j}^{\text{min}}(k|t)\}_{t \in \{t+1, \cdots, t+T\}}$.

**Find:**

$\{p_{h,j}^{\text{char}}(k)\}_{k \in \{t+1, \cdots, t+T\}}$.

**Which minimize:**

$$Z_h = \sum_{t=t+1}^{t+T} F_h(\tau) \tilde{W}_h^s(\tau) \Delta t + \alpha \sum_{t=t+1}^{t+T} \sum_{j=1}^{N_h} \left( s_{h,j}^+(k|t) + s_{h,j}^-(k|t) \right),$$

$$F_h(\tau) = \begin{cases} f_h^s(\tau) & \text{if } \tilde{W}_h^s(\tau) \geq 0, \\ f_h^p(\tau) & \text{if } \tilde{W}_h^s(\tau) < 0, \end{cases}$$

**Subject to:**

$$\forall k \in \{t+1, \cdots, t+T\},$$

$$\tilde{W}_h^s(k|t) = W_h^{\text{init}} + \sum_{j=1}^{N_h} p_{h,j}(k),$$

$$\tilde{W}_h^p(k|t) = W_h^{\max},$$

$$\sum_{t=t+1}^{t+T} \tilde{W}_h(k|t) \Delta t \leq J_h^{\text{max}},$$

$$\tilde{W}_h^s(0|t) + \sum_{j=1}^{N_h} p_{h,j}(0|k) \geq 0,$$

$$p_{h,j}^{\text{char}}(k) \gamma_{h,j}(k|t) = 0,$$

$$p_{h,j}^{\text{char}}(k) \leq p_{h,j}^{\text{max}}(k),$$

$$B_{h,j}^{\text{min}}(k) \leq B_{h,j}^{\text{max}}(k),$$

$$B_{h,j}(0|k) = B_{h,j}^{\text{init}}(k),$$

$$B_{h,j}(k) = B_{h,j}(k-1) + (1 - \gamma_{h,j}(k|t)) p_{h,j}^{\text{char}}(k|t) \Delta t,$$

$$\tilde{\gamma}_j(k|t) B_{h,j}^{\text{cons}}(k|t),$$

$$B_{h,j}(T_{h,j}^{\text{char}}) = B_{h,j}^{\text{max}},$$

$$s_{h,j}^+(k|t) - s_{h,j}^-(k|t) = p_{h,j}(k+1|t) - p_{h,j}(k|t),$$

$$s_{h,j}^+(k|t) \geq 0,$$

$$s_{h,j}^-(k|t) \geq 0.$$

The objective function (1) is the summation of electricity costs which is calculated from multiplying by consumed or surplus electricity $\tilde{W}_h(\tau)$ and a pricing coefficient $F_h(\tau)$. $\tilde{W}_h(\tau)$ is described as trading electricity at $\tau$ in the equation (2). Since $F_h(\tau)$ is switched with the cases of purchase or sale, it is divided into two cases whether $\tilde{W}_h(\tau)$ is positive or negative. If $\tilde{W}_h(\tau)$ is negative value, then the HEMS gets income at $\tau$. On the other case, the HEMS pays the electricity cost when $\tilde{W}_h(\tau)$ has positive value. Thus, the electricity cost is derived as a signed cost of $\tilde{W}_h(\tau)$.

The equation (3) shows the upper bound of $\tilde{W}_h(\tau)$. This bound is defined by the contract with an electric power company. The equation (4) is the upper bound of electricity consumption for 24 hours. This constraint prevents excessive consumption in home. The equation is mainly needed for such a case that the total electricity fee depends on the amount of electricity consumption for a month. In this paper, this constraint is not important because the electricity fee is decided only by periods of time. The equation (5) prevents the reverse power flow from the in-vehicle batteries to power grid.

The equation (6) is the constraint of charge/discharge permission for the vehicle battery considering driver’s schedule. When
the vehicle \( j \) is connected to home \( h \) (\( \gamma_{h,j}(kt) = 0 \)), the battery can charge/discharge. On the other hand, the battery cannot charge/discharge at home when the car is away from home \( h \) (\( \gamma_{h,j}(kt) = 1 \)). Equations (7) and (8) show charge/discharge performances per one step and minimum/maximum capacities of the battery \( j \), those parameters are determined by the property of the battery. Besides, the minimum battery capacity \( B_{h,j}^{\min}(k) \) means the minimum energy which the user requires at time \( t \). The equation (9) defines the initial value of the battery energy, and the (10) describes updating of the battery energy in each steps. In order to reset measurement error of state-of-charge (SOC), the battery has to be fully charged at the time \( T_{v,\text{char}} \) which is set with the equation (11).

The second member of the equation (1) is to add penalty for variation of charge/discharge power in successive time steps. This deference is expressed as the equation (12) with two auxiliary variables \( s^+_h(j)(kt) \) and \( s^-_h(j)(kt) \). Both values are positive by the constraints (13) and (14). The coefficient \( \alpha \) is small enough and positive.

2.2.3 MLDS formulation

This optimization problem is not classified as MILP because the objective function (1) has a conditional branch which depends on the sign of the variable \( \tilde{W}_h(j) \). Using a binary variable. The branching whether \( \tilde{W}_h(j) \) is positive or not is represented by \( \delta_h(\tau) \in \{0,1\} \) as follows:

\[
\begin{align*}
[\delta_h(\tau) = 1] & \leftrightarrow [\tilde{W}_h(j) \geq 0], \\
[\delta_h(\tau) = 0] & \leftrightarrow [\tilde{W}_h(j) < 0].
\end{align*}
\]

(15)

Here, an upper bound \( M \) and a lower bound \( m \) are set so as to satisfy \( m \leq \tilde{W}_h(j) \leq M \). The branching of the (15) is equivalently expressed as following inequalities:

\[
\begin{align*}
\tilde{W}_h(j) & \geq m(\delta(j) - 1), \\
\tilde{W}_h(j) & \leq M + e\delta(j) - \epsilon,
\end{align*}
\]

(16)

where \( \epsilon \) is a small positive value. The conditions (15) are realized as long as the inequalities (16) are satisfied. Using \( \delta_h(\tau) \), the first member of the objective function (1) is represented as follows:

\[
\begin{align*}
\sum_{\tau=t}^{t+T} F_h(\tau) \tilde{W}_h(j) \Delta t \\
= \sum_{\tau=t}^{T} \left( f^+_h(\tau) \tilde{W}_h(j) \delta_h(\tau) + f^-_h(\tau) \tilde{W}_h(j)(1 - \delta_h(\tau)) \right) \Delta t.
\end{align*}
\]

(17)

Here, this objective function is still nonlinear because \( \tilde{W}_h(j) \) and \( \delta_h(\tau) \) are decision variables in this optimization problem. To avoid the nonlinearity, the auxiliary variable \( z_h(\tau) \) is defined as \( z_h(\tau) = \tilde{W}_h(j) \delta_h(\tau) \). With this auxiliary variable \( z_h(\tau) \), the first member of the objective function (17) is represented as follows:

\[
\begin{align*}
\sum_{\tau=t}^{t+T} F_h(\tau) \tilde{W}_h(j) \Delta t \\
= \sum_{\tau=t}^{t+T} \left( (f^+_h(\tau) - f^-_h(\tau))z_h(\tau) + f^-_h(\tau) \tilde{W}_h(j) \right) \Delta t.
\end{align*}
\]

(18)

where \( z_h(\tau) \) satisfies following linear constraint:

\[
\begin{align*}
z_h(\tau) & \leq M \delta_h(\tau), \\
z_h(\tau) & \geq m \delta_h(\tau), \\
z_h(\tau) & \leq \tilde{W}_h(j)(\tau) - m(1 - \delta_h(\tau)), \\
z_h(\tau) & \geq \tilde{W}_h(j)(\tau) - M(1 - \delta_h(\tau)).
\end{align*}
\]

(19)

In this manner, the optimization problem is formulated as a MILP by MLDS formulation. Then, to solve this optimization problem, the optimized charge/discharge schedule can be obtained.

2.2.4 Example

To confirm the behavior of the model predictive HEMS with V2H, we show an example of simulation results for operating the HEMS in Fig. 4. In this case, the family has three people, an EV and a PV unit. The operation is for one day from 6:00 a.m. to the next 6:00 a.m. and the control period \( \Delta t \) is equal to 30 minutes, then, the total steps \( T \) is 48. The profile of the electricity consumption is from a database of Architectural Institute of Japan [16], and the profile of PV generation is calculated based on a database of volume of sunshine duration managed by Japan Meteorological Agency [17]. The profile of vehicle use is set as commuting and the full charge time of the in-vehicle battery \( T_{v,\text{char}} \) is at 6:00 a.m. The initial battery level \( B_{v,\text{init}} \) is equal to \( B_{v,\text{max}} \) and the \( B_{v,\text{max}} \) is set to 24. The prediction of electricity consumption \( \tilde{W}_h(j)(kt) \), PV generation \( \tilde{W}_h(j)(kt) \), and vehicle use \( \gamma_{h,j}(kt) \) are all known (these predictions have no error). The top figure is the electricity price \( f^{+}_h(\tau) \) for a day and the selling price \( f^{-}_h(\tau) \) is set to 48 JPY/kWh (although the price should be set to 31 JPY/kWh, the authors dare to use 48 JPY/kWh in order to show the behavior clearly). The electricity transitions of the purchase/sale and the charge/discharge for 24 hours are shown in the second and the third figures. The bottom figure is the fluctuation of the battery level.

Compared to “Without HEMS”, the electricity fee of “With HEMS” is reduced by 69.2 JPY (about 26.6 percent reduction)
per one day. In addition to the results, even if the predictions of electricity consumption and vehicle use have some errors, the HEMS is effective for the reduction of the electricity cost [10].

3. Model-Predictive BEMS

The authors have focused on BEMS for apartment buildings as the extension of the HEMS utilized in-vehicle batteries. In the BEMS, the authors consider a household as a component unit in an apartment building. Then, the authors rework a household to a home agent especially. Figure 5 illustrates the overview of the BEMS. There are some home agents at apartment floors, some PV units at the roof floor and some EV/PHVs owned by home agents individually at a parking space. Compared with the original HEMS, the BEMS has three different properties which are group optimization, electric power interchange and building load capacity. The three characteristics are described in following subsections.

3.1 Group Optimization

The first point is in the optimization of the schedule for charging/discharging. While the HEMSs individually optimize charge/discharging schedules of batteries for each home agent, the BEMS simultaneously schedules the charging/discharging for all in-vehicle batteries in group optimization. Thus, the BEMS needs all of the predicted profiles of the electricity consumption, generation and vehicle use for all of the home agents in the building.

3.2 Electric Power Interchange

The second point is the electric power interchange. Since the reverse power flow is forbidden and the electric power selling is permitted only from PV generator, the discharge power cannot be provided for the other home agents. Then, only inside of the BEMS, the authors permit the electric power interchange by controlling the demand and supply of the electricity in the same building.

3.3 Building Load Capacity

The third point is the limit of the building load capacity. This idea is simple. The BEMS has a power load limit by contract. By the group optimization under the limit, the BEMS can easily realize to cut the peak of electricity consumption which frequently occurs at the time when the electricity prices are low. This is because the batteries are apt to be charged with cheap electricity. In contrast, a group of HEMSs hardly keeps such a limit because each schedule of the charging/discharging are optimized individually.

3.4 Extension of Formulation

The BEMS has four differences as extension from the HEMS in formulation. The formulation of the BEMS described below and these differences from the formulation 2.2 are represented in the following sections.

Given: \( \{\bar{W}_h(k)[t], \bar{W}_h^*(k)[t], f_h^*(k), \bar{g}_h(k)[t], \bar{B}_{h,j}^{\text{const}}(k)[t], \bar{B}_{h,j}^{\text{init}}, \bar{B}_{h,j}^{\text{min}}(k)[k_1,\cdots,k_T], k=t+1,\cdots, t+T\}, \)

Find: \( \{\bar{p}_h(k)[k_1,\cdots,k_T], k=t+1,\cdots, t+T\}, \)

Which minimize:

\[
Z_g = \sum_{\tau=t+1}^{t+T} \left[ F_h(\tau)|\bar{W}_h(\tau)|\Delta t \right] + \alpha \sum_{\tau=t+1}^{t+T} \sum_{h=1}^{N_h} \sum_{j=1}^{N_j} \left[ s_h^+(k_0) \bar{s}_h^+(k_0) + s_h^-(k_0) \bar{s}_h^-(k_0) \right],
\]

subject to:

\[
\forall k \in \{t+1, \cdots, t+T\}, \forall h \in \{1, \cdots, H_g\}, (2)–(4), (6)–(14), \]

\[
\sum_{h=1}^{N_h} \bar{W}_h^+(k)[t] + \sum_{h=1}^{N_h} \sum_{j=1}^{N_j} p_{h,j}(k)[t] \geq 0, \]

\[
\bar{W}_h(k)[t] \leq W_{\text{max}}^h, \]

\[
\bar{W}_h(k)[t] = \sum_{h=1}^{N_h} \bar{W}_h(k)[t].
\]

3.4.1 Decision variables

Since the BEMS simultaneously optimizes and operates all of the charge/discharging schedule for each battery, the decision variables have to be calculated not only for single home agent but also for all of the home agents \( \forall h \in \{1, \cdots, H_g\} \), where \( H_g \) is the number of homes in the target apartment building. Then, the number of the decision variables increases from \( T \) to \( T \times H_g \).

3.4.2 Given parameters

In same manner for the extension of decision variables, given parameters also have to be obtained for all of home agents \( \forall h \in \{1, \cdots, H_g\} \), which are predicted profiles of electricity consumption, generation and vehicle use.

3.4.3 Objective function

The BEMS minimizes the total electricity fee \( Z_g \) for the apartment building as the group of home agents by group optimization, whereas the previous HEMS minimizes the electricity fee \( Z_h \) for a single home agent. The objective function (1) is replaced by (20). Where \( F_h(\tau) \) is a pricing coefficient at time \( \tau \) for the apartment building. The \( F_h(\tau) \) is switched with the cases of purchase or sale depending on whether \( W_h(\tau) \) is positive or negative in same manner as \( F_h(\tau) \). Pricing coefficients \( f_h(\tau) \) and \( f_h(\tau) \) are purchase and sale prices respectively.

In this optimization, the electricity fee for each home agent is not calculated in order to fix the number of binary variables.

---

Fig. 5 Overview of the proposed BEMS.
\( \delta_h(\tau), \) which achieves reduction of computational cost even though the decision variables increase \( H_g \) times. Therefore, these electricity fee should be calculated for each home with the other way according with some incentive of electric power interchange. This problem is a future work.

3.4.4 Constraints

All equations of the constraints also has to be set for all of home agents \( \forall h \in \{1, \ldots, H_g\} \). The electric power interchange is modified as (21) from the equation (5) for the permission of the reverse energy flow, and the building load capacity is simply expressed as (22). Where \( \hat{W}_g(k|t) \) is the total electricity consumption of the building in future time \( k \) predicted at time \( t \), and \( \hat{W}_g^{\max} \) is the power load limit of the building. The \( \hat{W}_g(k|t) \) is calculated as (23).

4. Computational Experiment

Through computational experiment, the usefulness of the proposed BEMS is verified by comparison with some cases.

4.1 Settings

The authors set a target apartment building that has 16 home agents. Each agent has a PV unit and an EV in which the \( B_{v,\text{max}}^{h,j} \) is 24 kWh. The operation is for one day from 6:00 a.m. to next 6:00 a.m. and the control period \( \Delta t \) is equal to 30 minutes, and the total steps \( T \) is 48. The upper bound of charging power \( p_{\text{char}}^{h,j} \) is set to 3 kW, and the lower bound of discharging power \( p_{\text{dis}}^{h,j} \) is set to \(-3 \) kW. The \( B_{v,\text{min}}^{h,j} \) is zero for all time. The electricity price \( f_g^+(t), B_{v,\text{init}}^{h,j} \) and \( T_{v,\text{char}}^{h,j} \) are same as the setting in the section 2.2.4, and \( f_g^-(t) \) is set to 31 JPY/kWh referred to the selling price for double generation in 2013 [18] with the exception of W/O EMS where the price is set to 38 JPY/kWh.

For electricity consumption, the authors prepare two profiles shown in Fig. 6. The horizontal axis is the time index and the vertical axis indicates electricity consumption. The first profile “Type A” has low level consumption, and the second profile “Type B” is high. These data are obtained in the database of Architectural Institute of Japan [16].

Figure 7 shows a profile of electricity generation calculated using a database system METPV-11 managed by New Energy and Industrial Technology Development Organization [19]. In this setting, the capacity of each PV unit assigned to each home is set to 1.5 kW considering the surface of the roof floor.

Two types profiles of vehicle use are shown in Fig. 8. The first profile “Type I” is used for commuting, and the second profile “Type II” is utilized for dropping off (the first drive), picking up (the third drive) and shopping (the second drive). In driving of EVs/PHVs, electricity consumptions of the in-vehicle batteries for commuting, dropping off, picking up and shopping are respectively set to 5.0 kWh, 0.5 kWh, 0.5 kWh and 1.0 kWh.

As a variety of home agents, the authors prepared five EMS types as follows:

- a group without EMS (written as W/O EMS),
- a HEMS group (written as HEMSx16),
- a BEMS enabled the electricity interchange (written as BEMS A),
- a BEMS with the upper bound of the power load (written as BEMS B) and
- a BEMS enabled the interchange and with the upper bound (written as BEMS C).

And also the authors prepared four settings of home agent groups shown in Table 1.

Group (a) has 8 home agents with the Type A of electricity consumption and the other 8 agents have the Type B. All of vehicle use profiles is Type I. Group (b) has the same electricity consumption as the group (a). All of vehicle use profiles is Type II. Group (c) has 8 home agents with the Type I of vehicle use and the other 8 agents are the Type II. All of electricity consumption is Type A. Group (d) has the same vehicle use settings as the group (c). All of electricity consumption is Type B.

![Fig. 6 Profiles of electricity consumption, “Type A” and “Type B”](image)

![Fig. 7 Profile of electricity generation by a PV unit.](image)

![Fig. 8 Profiles of vehicle use, “Type I” and “Type II”.](image)

<table>
<thead>
<tr>
<th>Electricity consumption</th>
<th>Type A</th>
<th>Type A</th>
<th>Type B</th>
<th>Type B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle use</td>
<td>Type I</td>
<td>Type II</td>
<td>Type I</td>
<td>Type II</td>
</tr>
<tr>
<td>Group (a)</td>
<td>8 homes</td>
<td>8 homes</td>
<td>8 homes</td>
<td>8 homes</td>
</tr>
<tr>
<td>Group (b)</td>
<td>8 homes</td>
<td>8 homes</td>
<td>8 homes</td>
<td>8 homes</td>
</tr>
<tr>
<td>Group (c)</td>
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<td>8 homes</td>
<td>8 homes</td>
<td>8 homes</td>
</tr>
<tr>
<td>Group (d)</td>
<td>8 homes</td>
<td>8 homes</td>
<td>8 homes</td>
<td>8 homes</td>
</tr>
</tbody>
</table>
Fig. 9 Charge/discharge electricity for the group (d) with the HEMSx16 (left) and BEMS A (right).

Fig. 10 Charge/discharge electricity for the group (d) with the BEMS B (left) and BEMS C (right).

Table 2 Electricity fee for 24 hours [JPY].

<table>
<thead>
<tr>
<th>Group</th>
<th>W/O EMS</th>
<th>HEMSx16</th>
<th>BEMS A</th>
<th>BEMS B</th>
<th>BEMS C</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a)</td>
<td>4570.25</td>
<td>4252.14</td>
<td>4252.84</td>
<td>4252.84</td>
<td>4252.84</td>
</tr>
<tr>
<td>(b)</td>
<td>4570.25</td>
<td>2487.85</td>
<td>2487.85</td>
<td>2600.85</td>
<td>2600.85</td>
</tr>
<tr>
<td>(c)</td>
<td>1878.03</td>
<td>1435.22</td>
<td>998.48</td>
<td>1451.97</td>
<td>998.48</td>
</tr>
<tr>
<td>(d)</td>
<td>7238.00</td>
<td>5292.06</td>
<td>4320.13</td>
<td>7024.82</td>
<td>6678.81</td>
</tr>
</tbody>
</table>

Table 3 Amount of electricity sold for 24 hours [kWh].

<table>
<thead>
<tr>
<th>Group</th>
<th>W/O EMS</th>
<th>HEMSx16</th>
<th>BEMS A</th>
<th>BEMS B</th>
<th>BEMS C</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a)</td>
<td>1.65</td>
<td>2.43</td>
<td>0.78</td>
<td>0.78</td>
<td>0.78</td>
</tr>
<tr>
<td>(b)</td>
<td>1.65</td>
<td>31.91</td>
<td>31.91</td>
<td>31.91</td>
<td>31.91</td>
</tr>
<tr>
<td>(c)</td>
<td>3.30</td>
<td>18.58</td>
<td>33.28</td>
<td>14.47</td>
<td>33.28</td>
</tr>
<tr>
<td>(d)</td>
<td>0.00</td>
<td>16.35</td>
<td>29.59</td>
<td>0.71</td>
<td>28.81</td>
</tr>
</tbody>
</table>

To confirm the usefulness of the proposed BEMS, we have carried out computational experiments and compared with the results of the five EMS types and the four agent groups. In the experiments, the prediction of electricity consumption $\tilde{W}_h(k|t)$, PV generation $\tilde{W}_h^{\text{PV}}(k|t)$ and vehicle use $\tilde{\gamma}_{h,j}(k|t)$ are all known (these predictions have no error).

4.2 Results

As the results of the computational experiment, amounts of electricity fee and amounts of electricity sold for 24 hours are respectively shown in Tables 2 and 3. The values in Table 2 are electricity fee and the values in Table 3 are sold electricity for each combination of the four group settings in the rows and the five EMS types in the column.

And the transitions of charge/discharge electricity of each EMS type for the agent group (d) are shown in Figs. 9 and 10. In these figure, “Time Index” axis indicates discrete time steps from 0 to 48, and “Agent ID” axis explains identification numbers of the home agents. The first 8 agents are Type B and Type I (written as Type B-I), the second 8 agents are Type B and Type II (written as Type B-II). The vertical axis illustrates charge/discharge electricity of in-vehicle batteries. The bottom surfaces in the figures show electricity of charge/discharge in gray scale heat map.

For computational time, the BEMS needs about 0.5 seconds for each control period in group optimization (using a computer installed Windows 7 which has Intel(R) Core(TM) i7-3770 CPU, 3.40GHz and 8GB memory). The computational cost is small enough to operate in real time. Even if the number of home agents is around a hundred, the cost is only about 6.0 seconds for each optimization step of the charge/discharge scheduling.

4.3 Discussion

With comparison of electricity fee in Table 2, the group (a) and the group (b) have no difference for all types. The reason is that the profiles of vehicle use are same pattern in these cases. The electricity interchange is not effective when an EV is at home, the other EVs are also at home.

On the other hand, for the group (c), the electricity fee of BEMS A where the electricity interchange enabled is reduced from 1435.22 to 998.48, that is 30.4 percent reduction in contrast with HEMSx16. Similarly, for the group (d), there is 18.4 percent reduction in the BEMS A from the HEMSx16.

For the group (c) in the results of BEMS B and BEMS C which have the upper bound of the power load, BEMS C reduced the electricity fee from 1451.97 to 998.48, that is 31.2 percent reduction in contrast with BEMS B. Similarly, for the group (d), BEMS C reduced the electricity fee from 7024.82 to 6678.81 in contrast with BEMS B. These results elucidate that the electricity interchange can reduce the electricity fee with a variety of vehicle use profiles even if the apartment building has the upper bound of the power load.

Table 3 shows the amount of electricity sold for each setting. In the group (c) and (d), the sold electricity of BEMS A is larger than HEMSx16, and the relation between BEMS B and BEMS C is the same. In Figs. 9 and 10, the right side cases BEMS A and BEMS C are enabled the electricity inter-
change, and these BEMS positively discharged the in-vehicle batteries (such as the black colored area) compared with the left side cases HEMS x 16 and BEMS B without the electricity interchange. Since the home agents of Type I, whose agent ID is 1 to 8, use vehicles for commuting, these batteries cannot discharge. In the cases enabled electricity interchange, the home agents of Type II, whose agent ID is 9 to 16, can utilize the in-vehicle batteries not only for themselves but also the other home agents. Consequently, the total amount of electricity sold increase in the apartment building.

These facts support that the reduction of the electricity fee has been accomplished by the mechanism of the electricity interchange.

5. Conclusion

In this paper, the authors presented the BEMS for apartment buildings in group optimization with electricity interchange using in-vehicle batteries. Through the computational experiment, the proposed BEMS has been verified as an useful system for energy management of apartment buildings. The electricity interchange from in-vehicle batteries based on group optimization can make big profit by reduction of the electricity fee when profiles of vehicle use are different in target building. In addition, even if the building has the upper limit of purchasing electricity, our proposed BEMS can reduce the electricity fee as possible under the limit.

In future work, because the BEMS can only calculate the total electricity fee without each billing of home agents, we should design incentive and mechanism for electricity interchange between home agents. The power trade will make changes behaviors of energy consumption of some or all home agents. In addition, we have to establish the robustness to operate the proposed BEMS in real world even if the prediction methods of electricity consumption, electricity generation and vehicle use have some error. To reach this goal, the BEMS requires estimation methods which enable to grasp the ranges of fluctuation and deviation of the three profiles in agent groups. If the fluctuation and the deviation can be bounded in controllable ranges, it will be able to operate actually.

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