Economic Evaluations of Residential Energy Systems Based on the Prediction-Operational Planning-Control Method using Time-of-Use Prices

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Abstract:

Demand-side electricity saving is an important factor in the reduction of the installed capacity of power-supply facilities. In order to save electricity automatically while maintaining comfort levels, home energy management systems (HEMS) have attracted attention. These systems can control residential energy equipment cooperatively to reduce electricity consumption while considering benefits to consumers. Although many researchers have evaluated HEMS, no one has conducted a study which considers the control of various types of residential energy equipment in real time along with the uncertainties of energy demands. This paper proposes a single HEMS method which connects prediction, operational planning and control steps and enables the evaluation of operational planning methods of HEMS connected with many kinds of residential energy equipment currently in use in Japan while considering the uncertainties. The purpose of this study is to evaluate the economic potential of residential energy systems based on the proposed method with the uncertainties of energy demands and photovoltaic (PV) output under time-of-use prices. The results allowed us to establish a framework to quantitatively evaluate the operational planning methods of HEMS with the uncertainties of energy demands and PV output. In addition, the usability of the proposed method was confirmed by comparing the operational costs to those of a reference method.

Keywords:

DR, HEMS, TOU prices, Residential Energy System, Demand, PV, Prediction, Optimization.

1. Introduction

In the past, surplus power-supply facilities have been built as a backup for supplying electricity in peak hours. It is very expensive to operate and maintain these facilities. Therefore, electricity saving on the demand side is important in order to reduce the installed capacity of power-supply facilities [1]. It is not rational to attempt to save electricity without considering the comfort of consumers. In an effort to save electricity automatically while maintaining comfort levels, attention has turned to home energy management systems (HEMS). HEMS are expected to control residential energy equipment automatically and cooperatively while considering benefits to consumers. From the perspectives of energy saving and cost saving, operational planning is important to a system including buffer equipment because there are a lot of alternate operational strategies for the buffer equipment. In addition, if a residential system consists of various types of residential energy equipment, it is more beneficial to control the equipment cooperatively as parts of a total optimization than to control the equipment independently as a number of partial optimizations. An optimization calculation to determine optimal operational strategies for residential energy equipment can be formulated as a mixed integer linear programming (MILP) problem. For instance, Yokoyama et al. [2] evaluated cogeneration systems using a MILP method. Wakui et al. [3] suggested that taking advantage of the high electricity-generating efficiency of the solid oxide fuel cell (SOFC) is more suitable for saving energy using a MILP method. However, the real-time demands are unclear until the moment in reality. Therefore, determination of operational strategy based on real-time demands is not for actual use. One of the solutions of this problem is to determine an operational strategy based on predictions of residential demands and PV output which are predicted in advance.

Surveys on energy management systems (EMS) or smart houses have been conducted by a number of researchers. Anvari-Moghaddam et al. [4] proposed a novel residential energy management system to improve energy consumption efficiency in regards to energy consumption costs and users' comfort using a mixed integer nonlinear problem (MINLP). Missaoui et al. [5] analysed a Building Energy Management System (BEMS) which optimizes a compromise between user comfort and electricity costs with a detailed house model. Pedrasa et al. [6] studied the usability of a coordinated, distributed energy-resource operation in a manner optimized to benefit users compared to the usability when they are scheduled independently. In addition, surveys taking uncertainty into consideration have also been reported. Yoshida et al. [7] evaluated the primary energy consumption of a residential photovoltaic/fuel-cell energy system using scenario-based stochastic programming to consider the uncertainty of residential demands. Multiple model-based predictive control was adapted to thermal energy storage by Kim [8]. Akbari et al. [9] illustrated a hospital energy management system which focused on uncertainties in demand, costs, and prices. Ozoe et al. [10] presented a mathematical model of a smart house using two-stage stochastic mixed-integer programming with uncertainties in PV output, and in the electricity and heat demands. Tascikaraoglu et al. [11] studied an experimental smart house, while forecasting the power available from renewable energy sources. Kawashima et al. [12] proposed an apartment building energy management system in a group optimization based on model-predictive control using in-vehicle batteries.

As for demand response (DR), which is another measure to realize peak shift or peak cut [1], Khan et al. [13] presented HEMS-enabled smart appliances to counter DR programs according to the comfort levels and priorities set by residents and also conducted some numerical simulations. Guo et al. [14] solved optimization problems for smart home scheduling with uncertainty of energy prices as a DR problem.

However, all of these researchers evaluated with only limited equipment configurations. Their suggestions might not assure the thermal comfort of residents. They also might not control residential energy equipment in real time. In this study, the term of control means operation of residential energy equipment to meet energy balance in real time. This paper proposes a method which connects prediction, operational planning and control steps as a HEMS method and enables evaluation of operational planning methods of HEMS connected with many kinds of residential energy equipment currently available in Japan while considering uncertainties. The purpose of this study is economic evaluation including the uncertainties of residential energy demands such as electricity, hot water (HW) and space heating/cooling, solar radiation including PV output, the temperature and humidity under time-of-use (TOU) prices as a DR problem assuring the thermal comfort of residents.

2. Methodology

An overview of the proposed *prediction-operational planning-control* method is shown in Fig. 1, and a data-flow diagram of both the proposed and reference methods is given in Fig. 2. As shown in

Fig. 1, first of all, in the prediction step, the next 24-hour insolation, bound by comfortable room temperature, the PV output and the residential energy demands are predicted based on external data [17-19]. Past data is used in order to predict the expected demand. Secondly, in the operational planning step and based on the prediction data, operational strategies for the residential energy equipment over the next 24 hours are optimally determined so as to minimize the daily operational costs. Finally, in the control step, following the strategies determined in the operational planning step, the residential energy equipment is controlled in order to meet the real-time energy demands. Then, the daily operational costs are calculated. As shown in Fig. 2, the prediction step is carried out between 12 a.m. and 1 a.m. Operational planning is carried out between 1 a.m. and 3 a.m. From 3 a.m. to 3 a.m. the following day, the control step is carried out. Then, in order to evaluate our method, the daily operational costs of the two methods are compared. The proposed method is assumed to consider HEMS function, so it is assumed that HEMS predicts the future demands and PV output and determines the operational strategies automatically, cooperatively, and optimally in this method. On the other hand, the reference method is not assumed to consider HEMS function, so there is no prediction step and operational strategies are assumed as individual and non-optimal in this method. In the operational planning and control steps, the predicted mean vote (PMV) [20], which is an index of the thermal comfort of people, is considered to meet the thermal comfort requirements of the residents.

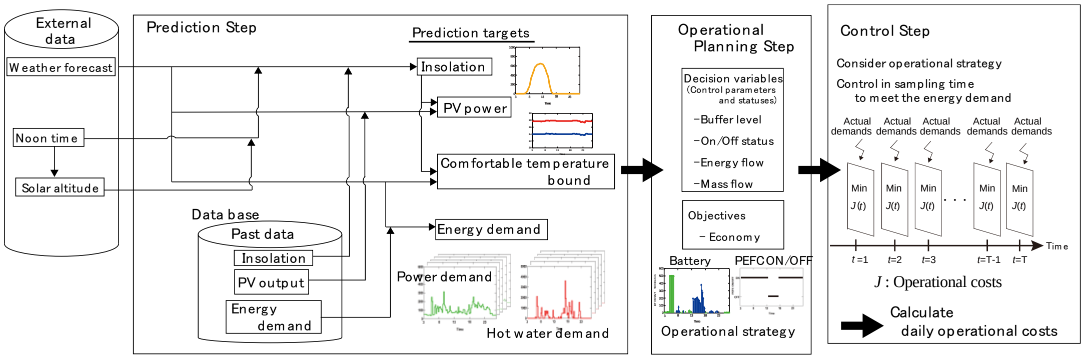

Fig. 1. Overview of the proposed prediction-operational planning-control method.

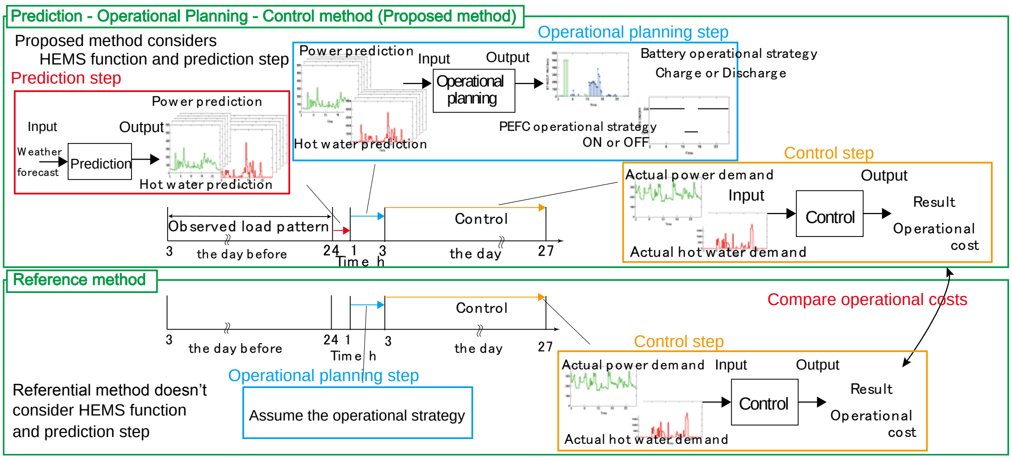

Fig. 2. Data flow of the proposed and reference methods.

2.1. Residential energy system

The residential energy system has options to include photovoltaics (PV), a battery (BT), a polymer-electrolyte-membrane fuel-cell cogeneration system (PEFC-CGS), a heat-pump water heater (HP), a condensing-gas boiler (CGB), air conditioning appliances (AC), thermal-insulation automatic blinds (TIB), sunlight-shielding automatic blinds (SSAB), and automatic windows (AW). A schematic diagram of the residential energy equipment and the specifications of each type of energy equipment used in this study are shown in Fig. 3. In this study, we ran economic evaluations based on the energy demands of an actual detached house and 12 equipment configurations. In this paper, the boundary of a residential energy system is defined as one household. Buying electricity from the grid and using city gas costs operating money. On the other hand, surplus electricity from the PV system can be sold to grid, and residents gain depending on the amount of surplus electricity sold to the grid. The equipment supplies electricity, HW, and heating/cooling. Electricity is supplied by the PV equipment, BT, PEFC-CGS, and electricity from the grid. HW is supplied by the CGB, PEFC-CGS, or HP, and both the PEFC-CGS and HP have hot-water tanks (HWT). Heating/cooling demands are satisfied by the AC equipment, TIB, SSAB and AW in order to fall inside the range of comfortable temperatures, which is set by the PMV.

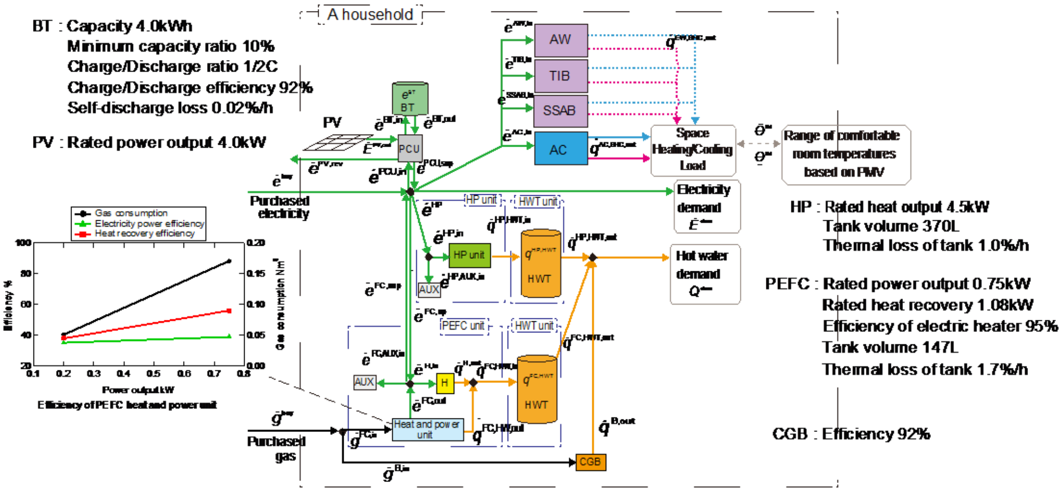

Fig. 3. A schematic diagram of residential energy systems and specifications.

In Fig. 3, the energy and mass flow rate is balanced at branch points for every sampling time, *t*. the constraints of this study are shown below. In this report, decision variables are given as lower-case alphabetical letters, excepting the time index, *t*, scenario number, *s*, efficiency, η, and objective value, *J*. Therefore, the decision variables consist of continuous energy and mass flow variables and 0-1 integer variables which represent the ON/OFF state of the equipment.

$$\dot{e}^{\mathrm{buy}}_{t,s} + \dot{e}^{\mathrm{FC,sup}}_{t,s} + \dot{e}^{\mathrm{PCU,sup}}_{t,s} = \dot{E}^{\mathrm{Dem}}_{t,s} + \dot{e}^{\mathrm{FC,up}}_{t,s} + \dot{e}^{\mathrm{HP}}_{t,s} + +\dot{e}^{\mathrm{AC,in}}_{t,s} + \dot{e}^{\mathrm{SSAB,in}}_{t,s} + \dot{e}^{\mathrm{TIB,in}}_{t,s} + \dot{e}^{\mathrm{AW,in}}_{t,s} + \dot{e}^{\mathrm{PCU,in}}_{t,s} \quad (1)$$

$$\dot{e}^{\mathrm{HP}}_{t,s} = \dot{e}^{\mathrm{HP,in}}_{t,s} + \dot{e}^{\mathrm{HP,AUX,,in}}_{t,s} \quad (2) \qquad \dot{e}^{\mathrm{FC,out}}_{t,s} = \dot{e}^{\mathrm{FC,sup}}_{t,s} + \dot{e}^{\mathrm{FC,AUX,in}}_{t,s} + \dot{e}^{\mathrm{H,in}}_{t,s} \quad (3)$$

$$\dot{q}^{\mathrm{HP,HWT,out}}_{t,s} + \dot{q}^{\mathrm{FC,HWT,out}}_{t,s} + \dot{q}^{\mathrm{CGB,out}}_{t,s} = \dot{Q}^{\mathrm{Dem}}_{t,s} \quad (4) \qquad \dot{q}^{\mathrm{FC,HWT,out}}_{t,s} + \dot{q}^{\mathrm{H,out}}_{t,s} = \dot{q}^{\mathrm{FC,HWT,in}}_{t,s} \quad (5)$$

$$\dot{g}^{\mathrm{buy}}_{t,s} = \dot{g}^{\mathrm{CGB,in}}_{t,s} + \dot{g}^{\mathrm{FC,in}}_{t,s} \quad (6)$$

Where $\dot{e}^{\mathrm{buy}}$ is the electricity purchased from the grid, $\dot{e}^{\mathrm{FC,sup}}$ and $\dot{e}^{\mathrm{PCU,sup}}$ are the electricity supplied from the PEFC-CGS and the power conditioning unit (PCU) respectively, $\dot{E}^{\mathrm{Dem}}$ is the electricity demand, $\dot{e}^{\mathrm{FC,up}}$ $\dot{e}^{\mathrm{HP}}$, $\dot{e}^{\mathrm{AC,in}}$, $\dot{e}^{\mathrm{SSAB,in}}$, $\dot{e}^{\mathrm{TIB,in}}$, $\dot{e}^{\mathrm{AW,in}}$, $\dot{e}^{\mathrm{HP,in}}$, $\dot{e}^{\mathrm{HP,AUX,in}}$, $\dot{e}^{\mathrm{FC,AUX,in}}$, and $\dot{e}^{\mathrm{H,in}}$ are the electricity consumed by the PEFC-CGS to start up, the HP, the AC, the SSAB, the TIB, the AW, the HP heating unit, the auxiliary (AUX) of the HP, the AUX of the PEFC-CGS and the electrical heater (H), respectively, $\dot{e}^{\mathrm{PCU,in}}$ is the electricity input to the PCU, $\dot{e}^{\mathrm{FC,out}}$ is the electricity output from the PEFC-CGS, $\dot{q}^{\mathrm{HP,HWT,out}}$, $\dot{q}^{\mathrm{FC,HWT,out}}$, $\dot{q}^{\mathrm{CGB,out}}$, and $\dot{q}^{\mathrm{H,out}}$ are the HW output from the HWT of the HP, the HWT of the PEFC-CGS, the CGB and the H respectively, $\dot{Q}^{\mathrm{Dem}}$ is the HW demand, $\dot{q}^{\mathrm{FC,HWT,in}}$ is the HW input to the HWT of the PEFC-CGS, $\dot{g}^{\mathrm{buy}}$ is the gas purchased, and $\dot{g}^{\mathrm{CGB,in}}$ and $\dot{g}^{\mathrm{FC,in}}$ are the gas consumption of the CGB and PEFC-CGS, respectively.

The output of each piece of equipment, including the PEFC, HP, H, AC, PCU and CGB is calculated by multiplying the input by the efficiency of each piece. The equations are below.

$$\dot{e}_{t,s}^{\mathrm{FC,out}} = \eta^{\mathrm{FC,E}} \dot{g}_{t,s}^{\mathrm{FC,in}} \quad (7)$$

$$\dot{q}_{t,s}^{\mathrm{FC,out}} = \eta^{\mathrm{FC,HW}} \dot{g}_{t,s}^{\mathrm{FC,in}} \quad (8)$$

$$\dot{q}_{t,s}^{\mathrm{HP,HWT,in}} = \eta^{\mathrm{HP,HW}} \dot{e}_{t,s}^{\mathrm{HP,in}} \quad (9)$$

$$\dot{q}_{t,s}^{\mathrm{H,out}} = \eta^{\mathrm{H,HW}} \dot{e}_{t,s}^{\mathrm{H,in}} \quad (10)$$

$$\dot{q}_{t,s}^{\mathrm{AC,SHC,out}} = \eta^{\mathrm{AC,SHC}} \dot{e}_{t,s}^{\mathrm{AC,in}} \quad (11)$$

$$\dot{e}_{t,s}^{\mathrm{PCU,sup}} + \dot{e}_{t,s}^{\mathrm{BT,in}} + \dot{e}_{t,s}^{\mathrm{PV,rev}} = \eta^{\mathrm{INV}} (\dot{e}_{t,s}^{\mathrm{PCU,in}} + \dot{e}_{t,s}^{\mathrm{BT,out}} + \dot{E}_{t,s}^{\mathrm{PV}}) \quad (12)$$

$$\dot{q}_{t,s}^{\mathrm{CGB,out}} = \eta^{\mathrm{CGB,HW}} \dot{g}_{t,s}^{\mathrm{CGB,in}} \quad (13)$$

Where $\eta^{\mathrm{FC,E}}$, $\eta^{\mathrm{FC,HW}}$, $\eta^{\mathrm{HP,HW}}$, $\eta^{\mathrm{H,HW}}$, $\eta^{\mathrm{AC,SHC}}$, η^{INV}, and $\eta^{\mathrm{CGB,HW}}$ are the generation efficiency of the PEFC, the efficiency of the PEFC for heat recovery, the efficiency of the HP, the efficiency of the H, the efficiency of the AC for heating/cooling, the efficiency of the inverter of the PCU, and the efficiency of the CGB, respectively, $\dot{q}^{\mathrm{HP,HWT,in}}$ is the HW input to the HWT of the HP, $\dot{q}^{\mathrm{AC,SHC,out}}$ is the thermal supply from the AC, $\dot{e}^{\mathrm{BT,in}}$ and $\dot{e}^{\mathrm{BT,out}}$ are the charge and discharge electricity of the BT, respectively, $\dot{e}^{\mathrm{PV,rev}}$ is the electricity from the PV sold to the grid and $\dot{E}^{\mathrm{PV}}$ is the PV output.

The storage energy level of the HWT and BT is calculated by the equations below.

$$q_{t,s}^{\mathrm{FC,HWT}} = \left(1 - \eta^{\mathrm{FC,HWT,loss}} \delta t\right) q_{t-1,s}^{\mathrm{FC,HWT}} + \dot{q}_{t,s}^{\mathrm{FC,HWT,in}} - \dot{q}_{t,s}^{\mathrm{FC,HWT,out}} \quad (14)$$

$$q_{t,s}^{\mathrm{HP,HWT}} = \left(1 - \eta^{\mathrm{HP,HWT,loss}} \delta t\right) q_{t-1,s}^{\mathrm{HP,HWT}} + \dot{q}_{t,s}^{\mathrm{HP,HWT,in}} - \dot{q}_{t,s}^{\mathrm{HP,HWT,out}} \quad (15)$$

$$e_{t,s}^{\mathrm{BT}} = \left(1 - \eta^{\mathrm{BT,loss}} \delta t\right) e_{t-1,s}^{\mathrm{BT}} + \eta^{\mathrm{BT}} \dot{e}_{t,s}^{\mathrm{BT,in}} - \eta^{\mathrm{BT}} \dot{e}_{t,s}^{\mathrm{BT,out}} \quad (16)$$

Where $q_{t,s}^{\mathrm{FC,HWT}}$, $q_{t,s}^{\mathrm{HP,HWT}}$ and $e_{t,s}^{\mathrm{BT}}$ are the storage energy levels of the HWT of the PEFC-CGS, the HWT of the HP, and the BT, respectively, $\eta^{\mathrm{FC,HWT,loss}}$, $\eta^{\mathrm{HP,HWT,loss}}$, $\eta^{\mathrm{BT,loss}}$, and η^{BT} are the loss factors of the HWT of the PEFC-CGS, the HWT of the HP, the BT, and the charge/discharge efficiency of the BT, respectively, and δt is the sampling time interval.

2.2. Proposed method (Prediction-Operational Planning-Control)

In this section, we explain the proposed *prediction-operational planning-control* method which considers HEMS function as shown in Fig. 2. Therefore, the operational strategies of the energy equipment are optimally determined based on prediction data. The term of control means the operation of the residential energy equipment to meet the real-time energy balance.

2.2.1. Prediction step

In the prediction step, databases of demand and climate conditions are constructed. We develop a prediction system which searches for similar patterns in the databases to input. A Just-in-Time (JIT) modelling method is used to develop the proposed prediction system, and the demand of the previous day and the weather forecast are input to the databases. The prediction systems developed by commonly used methods such as linear regression models cannot consider various uncertainties caused by unexpected human activities. Therefore, the operational strategies based on these predictions might not be robust. To make the operational strategies more robust, a prediction system which can output multiple prediction data is useful. Thus, we adopt a JIT modelling method based on the k-means method for prediction and our proposed prediction system can output several realistic scenarios considering various human activities. It is the same for insolation and PV output prediction in the sense that we can consider confidence intervals. However, the confidence intervals of insolation and PV output are not considered in this paper.

The next 24-hour temperature and humidity are predicted by an external data service, namely the Japan Meteorological Business Support Center. The insolation for the next 24 hours, the PV output, and the residential energy demands are predicted based on past data using the proposed prediction system [17-19]. First, a database of input-output relationships is constructed using the JIT modelling method based on actual observed values of an actual detached house. Secondly, we select several data points which are similar to inputs from the database. Finally, we output data for several prediction targets which are estimated by the selected data points. In this prediction method, Metric Learning is applied to learn degrees of similarity of distances between input data and data in the database except for the data of the prediction day. We input the temperature and humidity forecast for the prediction day and the energy demands observed from the previous day into the database.

2.2.2. Operational planning step

Stochastic Programming (SP), which is based on scenarios, is applied to the optimal operational planning problem to make operational strategies robust by considering several predicted data scenarios for operational planning. Scenarios are the energy demands for the next 24 hours, the PV output, and the range of comfortable room temperatures time-series data, which are integrated over 15 minute segments. In SP, formulation as a MILP is possible by considering future events as scenarios with event probabilities. A brief overview of SP is given in Fig. 4.

As shown in Fig. 2, in the operational planning step, 24-hour operational strategies for an evaluation period from 3 a.m. to 3 a.m. the next day are determined between 1 a.m. and 3 a.m. An evaluation day is represented by the time index $t = 1, \ldots, T$ by dividing the evaluation period into T parts as sampling time. Thus, T represents the number of sampling time periods. We assume that $T = 96$; thus, the sampling time interval is 15 minutes. This is formulated as a large-scale MILP problem which consists of 14238 decision variables and 15524 constraints for one day of one energy system.

As shown in Fig. 4, we minimize the expected value $\bar{J}^{\mathrm{SP}}$ of the daily operational costs J_s^{SP} of S scenarios. The objective function is shown in Equations (17) and (18). The inputs are the predicted temperature, humidity, the PV output data scenario, and scenarios for the electricity and HW demands which are represented by the number of scenario $s = 1, \ldots, S$ with event probabilities P_s . Thus, S represents the total number of scenarios. In this study, the event probabilities P_s are equal to each scenario and the sum of P_s equals one. S is assumed to be five scenarios. Additionally, in order to determine the same operational strategies for each discretized time from many different scenarios, constraints of Equations (19) to (22) below are added. As for heating/cooling demands, the range of comfortable room temperatures which is decided by the PMV is satisfied by the AC, TIB, SSAB and AW.

$$Min \bar{J}^{SP} = \sum_{s=1}^{S} P_s \; J_s^{SP} \tag{17}$$

$$J_s^{SP} = \sum_{t=1}^{T} (C_{t,s}^{e} \dot{e}_{t,s}^{buy} + C_{t,s}^{g} \dot{g}_{t,s}^{buy} - C_{t,s}^{rev} \dot{e}_{t,s}^{PV,rev}) \tag{18}$$

$$z_{t,s=1}^{\mathrm{PEFC}} = z_{t,s=2}^{\mathrm{PEFC}} = \cdots = z_{t,s=S}^{\mathrm{PEFC}} \tag{19}$$

$$\dot{\mathrm{e}}_{t,s=1}^{\mathrm{BT,in}} = \dot{\mathrm{e}}_{t,s=2}^{\mathrm{BT,in}} = \cdots = \dot{\mathrm{e}}_{t,s=S}^{\mathrm{BT,in}} \tag{20}$$

$$\dot{\mathrm{e}}_{t,s=1}^{\mathrm{BT,out}} = \dot{\mathrm{e}}_{t,s=2}^{\mathrm{BT,out}} = \cdots = \dot{\mathrm{e}}_{t,s=S}^{\mathrm{BT,out}} \tag{21}$$

$$\dot{q}_{t,s=1}^{\mathrm{HP,HWT,in}} = \dot{q}_{t,s=2}^{\mathrm{HP,HWT,in}} = \cdots = \dot{q}_{t,s=S}^{\mathrm{HP,HWT,in}} \tag{22}$$

Where C^{e} , C^{g}, C^{rev}, and z^{PEFC} are the time-of-use prices of the electricity, the metered cost of the gas, the feed-in tariff for the PV reversed electricity, and the PEFC ON/OFF integer state, respectively.

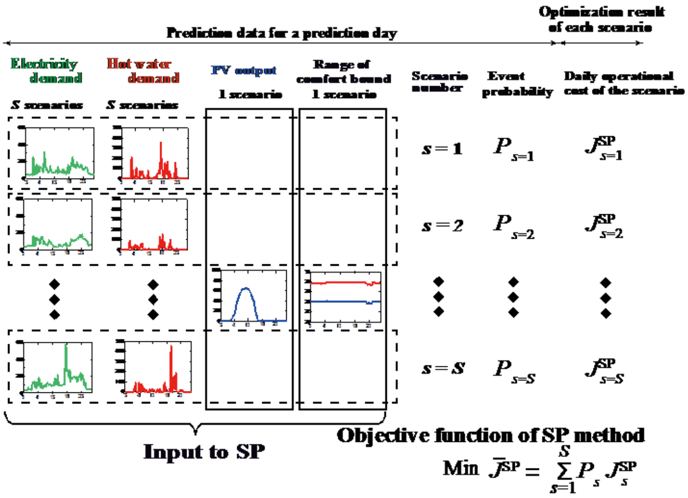

Fig. 4. A brief overview of the SP method.

2.2.3. Control step

An image of the control step is shown in Fig. 5. The control problem in real time is structured as solving the MILP by sampling time. As shown in Fig. 5, in order to control the equipment in real time, the operational cost in the sampling time is minimized in this control step, in contrast to the operational planning step in which the daily operational cost is minimized. That is, the control problem in real time is an optimal energy-supply problem by sampling time t = 1, ..., T, repeatedly. Then, the daily operational cost is calculated. The inputs are real-time actual weather data, the PV output data, and the energy demands. The constraints of this optimal energy-supply problem consist of the energy and mass flows, that is, Equations (1) to (16), the specifications of the energy systems and the range of comfortable room temperatures from the PMV. The decision variables are the same as those in the operational planning step (section 2.2.2). Additionally, in the control step, the operational strategies of the energy equipment and the initial values of the buffers from the operational planning step are input as constraints. These additional constraints are shown in Table 1. In Table 1, variables with superscript 'Plan' represent operational strategies determined in the operational planning step, and variables without superscript 'Plan' represent decision variables in this control step. In order to have leeway in operating the energy equipment, the constraints in Table 1 consist of inequalities. The objective function of this paragraph is shown below. Operational costs in the sampling time are minimized.

$$\mathrm{Min}\, J_t = C_t^{\mathrm{e}} \dot{e}_t^{\mathrm{buy}} + C_t^{\mathrm{g}} \dot{g}_t^{\mathrm{buy}} - C_t^{\mathrm{rev}} \dot{e}_t^{\mathrm{PV,rev}} \tag{23}$$

Table 1. Additional constraints for the control step.

Equipment	Target variables	Constraint
Battery (BT)	Output electricity from BT	$\dot{e}_t^{BT,out} \leq \dot{e}_t^{BT,out,Plan}$
	Input electricity into BT	$\dot{e}_t^{BT,in} \geq \dot{e}_t^{BT,in,Plan}$
Heat pump water heater (HP)	Input heat into HWT from HP	$\dot{q}_t^{HP,HWT,in} \geq \dot{q}_t^{HP,HWT,in,Plan}$
Polymer electrolyte membrane fuel cell (PEFC)	PEFC ON/OFF state	$z_t^{PEFC} \geq z_t^{PEFC,Plan}$

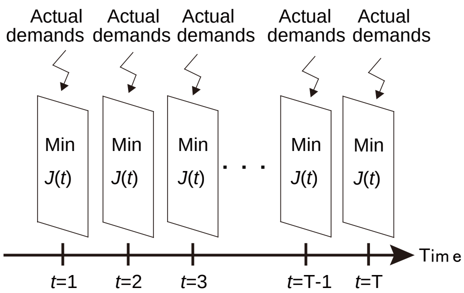

Fig. 5. An image of the control step.

2.3. Reference method

In this section, we construct a method which does not consider HEMS functions, as shown in Fig. 2. That is, the residential energy equipment cannot predict future events, communicate with each other through the HEMS, and get DR signals. The operational strategies of the energy equipment are determined in advance based on the operation modes of real machines, without prediction data and optimal operational planning. This method is compared with our proposed *prediction-operational planning-control* method later.

2.3.1. Operational planning step

Equipment such as the BT, PEFC and HP need operational strategies, and the assumed operational strategies of the residential energy equipment are shown in Table 2. Additionally, the initial values of the buffers are set to their minimal values. The assumed operational strategies are input to the control step explained in the next section. On the other hand, equipment such as the CGB and PV do not need operational strategies because the CGB simply follows the HW demand, which is not supplied by other equipment, and the PV output is not a decision variable in this study.

2.3.2. Control step

The control step in this paragraph is the same as the control step of our proposed method (section 2.2.3).

3. Settings

The real-time electricity and HW demands and PV output are actual, observed values taken from an existing, detached house on 12 representative days. As the past data for demand and PV predictions, annual measurement values from the same house are used, and the temperature, humidity and insolation data, which are publicly available, are used for the predictions.

The floor plan of the model of the residential space and specifications are shown in Fig. 6. This house model is made of wood on the inside and heat-insulating materials on the outside, and has HIB, SIB and EW on the north, south, east and west sides. The temperature of the living space falls inside the range of comfortable temperatures which is decided by PMV.

Table 2 shows the costs of electricity and city gas for various conditions and the profit from any electricity sold from the PV equipment back to the grid.

We assume that the house has the energy equipment shown in Table 3. The operational strategies of the residential energy equipment assumed for the reference method are also shown in Table 3 based on the operation mode of real machines. The AC, HIB, SIB and EW are skipped because they are included in all equipment configurations.

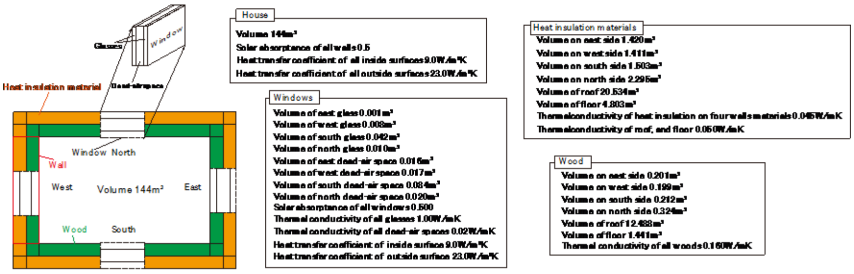

Fig. 6. The floor plan of the model of the residential space.

Table 2. Costs of electricity and city gas for various conditions as well as the profit from the electricity sold from the PV.

Type	Kind of costs	Conditions	Value	Unit
Grid [21]	Basic cost	—	1296	Yen/month
	Fuel regulatory cost	—	2.35	Yen/kWh
	Metered costs	7:00-13:00	28.99	Yen/kWh
		13:00-16:00	54.68	Yen/kWh
		16:00-23:00	28.99	Yen/kWh
		23:00-7:00	12.16	Yen/kWh
Gas [22]	Basic costs	Without CGB	1026	Yen/month
		With CGB	1458	Yen/month
	Metered costs	Without CGB	156.11	Yen/Nm^3
		With CGB	134.51	Yen/Nm^3
PV [23]	Feed-in tariff (FIT)	For surplus electricity	37.00	Yen/kWh

Table 3. Equipment configurations and operational strategies of residential energy equipment based on the real machines assumed for the reference method.

No.	System name	Equipment configuration	Assumed operational strategies
1	CGB	CGB	none
2	BT+CGB	BT, CGB	The BT charges fully until 07:00
3	HP	HP	The HP stores thermal energy up to 30% of the maximum capacity of the HWT until 07:00
4	BT+HP	BT, HP	The BT follows No. 2 and the HP follows No. 3
5	PEFC	PEFC-CGS	The PEFC generates electricity from 04:00 to 24:00
6	BT+PEFC	BT, PEFC-CGS	The BT follows No. 2 and the PEFC follows No. 5
7	PV+CGB	PV, CGB	none
8	PV+BT+CGB	PV, BT, CGB	The BT follows No. 2
9	PV+HP	PV, HP	The HP follows No. 3
10	PV+BT+HP	PV, BT, HP	The BT follows No. 2 and the HP follows No. 3
11	PV+PEFC	PV, PEFC-CGS	The PEFC follows No. 5
12	PV+BT+PEFC	PV, BT, PEFC-CGS	The BT follows No. 2 and the PEFC follows No. 5

4. Numerical simulation result

The daily operational cost reductions, ϕ^{cost} yen/day, between our proposed method and the reference method, are defined below as an evaluation index.

$$\phi^{cost} = J^{ref} - J^{pro} \tag{8}$$

Where J^{ref} and J^{pro} are the daily operational costs of the reference method and the proposed method, respectively.

This study compares not the systems but the methods. The daily operational cost reduction, ϕ^{cost}, of the energy systems are shown in Fig. 7. This shows the maximum value, the 75$^{\text{th}}$ percentile, the median value, the 25$^{\text{th}}$ percentile, and the minimum value of ϕ^{cost} from above. As can be seen in Fig. 7, the median values of operational cost reduction are positive except for the HP and PV+HP systems. The maximum median value of operational cost reduction is 51 yen/day by the BT+CGB. This is because the BT in the proposed method can discharge at the times when the electricity prices are high. In the proposed method, the operational strategies of BT are planned to discharge at the times when the electricity prices are high based on TOU prices and predicted demand data. On the other hand, in the reference method, TOU prices are not considered in the operational planning step. Therefore, the BT charges at times when the electricity price is low and discharges at once in order to minimize any losses due to self-discharge. Fig. 8 shows the demand scenarios and operation results of the PEFC-CGS over one day. Fig. 8(a) shows an actual and five predicted electricity demand scenarios and the PEFC ON/OFF state. Fig. 8(b) shows an actual and five predicted HW demand and thermal scenarios for the HWT. In Fig. 8, the mismatches between the five scenarios of predicted demands and actual demands of both electricity and HW are clear. However, the proposed method reduced operational costs by 24 yen/day compared to the reference method which does not include a prediction step. When deciding operational strategies in the operational planning step, the proposed method input five realistic predicted demand scenarios and minimized the expected operational cost of each of them. That is, the operational strategy is robust for mismatches between the predicted energy demands and actual energy demands.

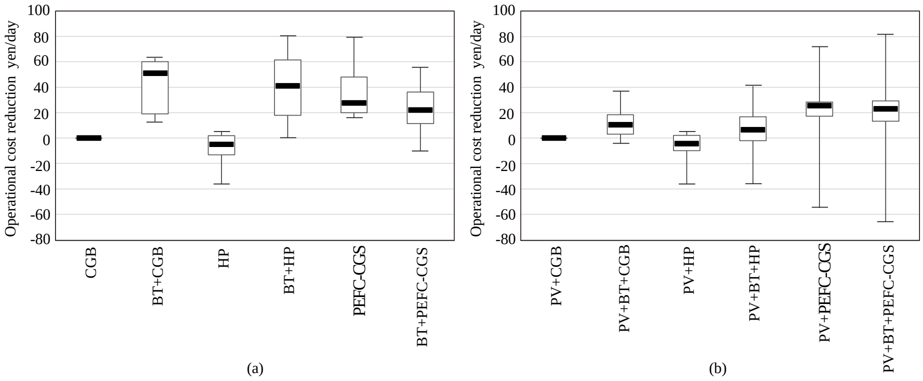

Fig. 7. The daily operational cost reduction of each energy system (comparison of the methods); (a) the systems without PV; (b) the systems with PV.

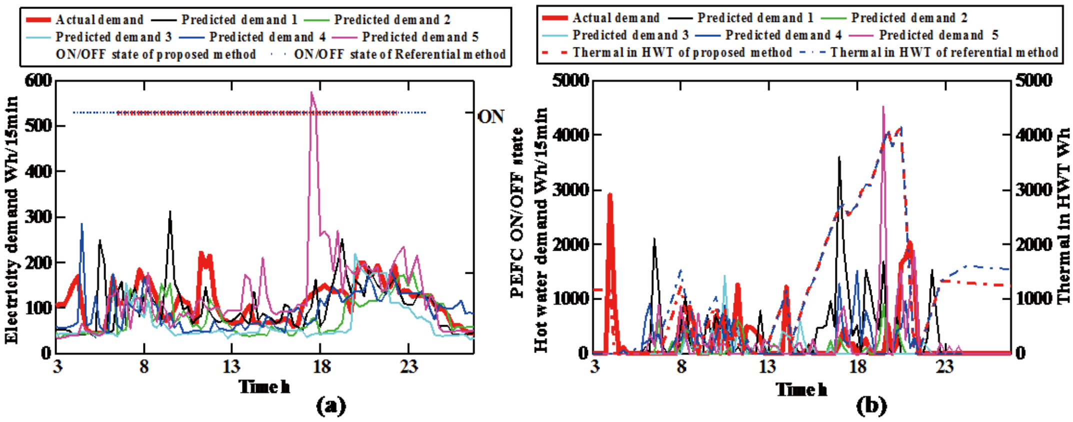

Fig. 8. Demand scenarios and operation results for the PEFC-CGS over one day; (a) an actual and 5 predicted electricity demand scenarios and the PEFC ON/OFF state; (b) an actual and 5 predicted HW demand and thermal scenarios for HWT.

5. Conclusion

The objective of this study was to evaluate economic potentials while including uncertainties of energy demands and PV output, TOU prices, and the thermal comfort of residents. We established a method which connects prediction, operational planning, and control steps to consider uncertainties of energy demands and PV output as a base of HEMS.

We established a new method which connects prediction, operational planning and control steps as a base of HEMS and enabled the quantitative evaluation of operational planning methods of HEMS with uncertainties of energy demands and PV output. Through the computational experiment, the BT can reduce costs by about 50 yen/day by discharging at times when electricity prices are high. The PEFC-CGS can reduce costs by about 25 yen/day by operating effectively.

In future work, we have to improve the proposed method by additional computational experiments with more calculation conditions such as demand data, electricity prices, and other house profiles. In addition, we should establish a framework to analyse the optimal operational strategies in a community for various exogenous conditions such as fee schedules and power grid constraints.

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Nomenclature

C	cost conversion factor, yen/Wh
e	electricity storage level, Wh
$\dot{e}$	electricity flow rate, Wh/15min
$\dot{g}$	gas flow rate, Wh/15min
J	objective function, operational cost
P	probability
q	heat storage level, Wh
$\dot{q}$	heat flow rate, Wh/15min
s	scenario index
S	total number of scenario
t	time index
T	total number of sampling period
z	0-1 integer state of equipment

Greek symbols

δt	sampling time interval, hour
η	efficiency, %
θ	temperature, ℃
ϕ	evaluation index

Superscripts and abbreviations

AC	air conditioner
AUX	auxiliary
AW	automatic window
BT	battery
buy	purchased
cost	cost
CGB	condensing gas boiler
dem	demand
DR	demand response
e	electricity
EMS	energy management system
FC	fuel cell
FIT	feed-in tariff
g	gas
H	electrical heater
HEMS	home energy management system
HP	heat pump water heater
HW	hot water
HWT	hot water tank
in	input
INV	inverter
loss	loss
MILP	mixed integer linear programming
out	output
PCU	power conditioning unit
PEFC-CGS	polymer electrolyte membrane fuel cell cogeneration system
Plan	determined in operational planning step
PMV	predicted mean vote
pro	proposed method
PV	photovoltaic
ref	reference method
rev	reversed
SHC	space heating and cooling
SOFC	solid oxide fuel cell
SP	stochastic programming
SSAB	sunlight shielding automatic blind
sup	supply
TIB	thermal insulation automatic blind

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