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Article

Optimizing Re-planning Operation for Smart House Applying Solar Radiation Forecasting

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Abstract: This paper proposes the re-planning operation method using Tabu Search for direct current (DC) smart house with photovoltaic (PV), solar collector (SC), battery and heat pump system. The proposed method is based on solar radiation forecasting using reported weather data, Fuzzy theory and Recurrent Neural Network. Additionally, the re-planning operation method is proposed with consideration of solar radiation forecast error, battery and inverter losses. In this paper, it is assumed that the installation location for DC smart house is Okinawa, which is located in Southwest Japan. The validity of proposed method is confirmed by comparing the simulation results.

Keywords: DC smart house; forecast error; re-planning operation; photovoltaic; solar collector

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1. Introduction

In the background of fossil fuel depletion and increasing global warming caused by high carbon dioxide density in the atmosphere, power production plants using renewable energy have attracted international attention. In the case of electric power suply in isolated islands of Japan, renewable energy power production plants will be installed in many isolated islands in the near future to replace the fuel-consuming diesel generators.

This paper presents an optimal operation method for the DC (direct current) grid system (DC smart house) with PV (photovoltaic) and SC (solar collector), assuming that the installation location for the DC smart house is Okinawa. Okinawa has about 40 isolated islands located in Southwest Japan. These islands mostly depend on diesel generators for power supply due to the long distance to the mainland of Okinawa and their small areas. If it is possible to provide power load and heat load by PV with SC in the DC grid system, the consumers can then enjoy more advantages [1]. However, the solar radiation forecast errors were not considered in our previous work. Though some researchers have proposed a solar radiation forecasting method using weather prediction [2], the electrical loss of inverter and efficiency of battery charge/discharge were not considered. This paper presents a re-planning operation method using Tabu Search for DC smart house considering solar radiation forecast error, battery and inverter losses. Simulation results show that daily running costs are minimized by the proposed method on sunny and rainy days. Once the proposed methods become widely applied, they will be able to contribute to society as a global warming prevention technology by a positive introduction of renewable energy systems.

It is well known that photovoltaic (PV) systems are capable of generating electricity in a clean, quiet and reliable way, but the power output fluctuation depends on weather conditions. From the point of view of energy storage, batteries are integrated with a PV system for providing energy to load during night time and sunless period. Nowadays, a new home energy management system (HEMS) with PV, windmill, and electrical storage system has been reported in [3]. Additionally, feed-in-tariffs [4] for residential PV systems are introduced in many countries. Furthermore, solar collector (SC) and heat pump (HP) systems are developed in the heat supply [5]. An advanced efficient utilization method of these renewable systems is important for utilizing solar energy [6]. Solar radiation forecasting [7] is an important tool for determining the amount of storage battery energy, PV power output, and heat thermal energy collection of SC. The power conversion system is usually alternate current (AC) in electric power companies. However, a direct current (DC) grid system [8] for residential housing has been the focus of recent years. In a typical residential house, power load and heat load are the most important factors. Since the DC grid has lower power loss than that of the AC grid system, usually a stand-alone photovoltaic power system is designed and implemented to operate residential DC power appliances such as lamps, heat load, *etc*.

Recently, many related works about energy management for smart house have been reported. Pedrasa *et al.* introduced enhancements to an energy service decision-support tool that aims to aid households in making more intelligent decisions when operating their major home appliances due to maximizing the net benefits gained by the end users [9]. Kanchev *et al.* presented an energy management system for a microgrid, including PV with embedded storage units and a gas microturbine [10]. The operational planning is based on the PV power output forecasting. A local controlling algorithm was proposed in [11] to control domestic electricity and heat demand. The algorithm of planning is based on the current state of the system and on the external condition on heat demand. Adika and Wang presented the energy management of a single household that is equipped with a grid tied rooftop PV system and a set of devices [12]. The main idea is to encourage customers to participate in energy generation and efficient electricity consumption. Our current work also takes into account the concept of efficient energy managements mentioned in these above, but the approach of operational planning is different.

This paper is organized as follows: Section 2 introduces the proposed DC smart house, which includes PV, SC, battery and heat pump system. In Section 3, the optimization method for re-planning operation using Tabu Search is described. Section 4 explains method to determine battery capacity. Section 5 gives a brief explanation of the PV power output forecasting. Section 6 shows the simulation results. Finally, Section 7 concludes.

2. DC Smart House

Figure 1 shows the assumed DC smart house model in this paper. In our previous work [1], a heat pump system was not included. The heat pump system in FIgure 1 is connected to hot-water storage tank and that system heated by general electric power system or battery energy. The inverter between power system and DC bus is assumed to be a bi-directional inverter. Table 1 shows the system capacities. The simulation result is based on the assumption that conversion efficiencies of battery η_{bat} and inverter η_{inv} are 91%, 90%, respectively.

Figure 1. DC Smart house model.

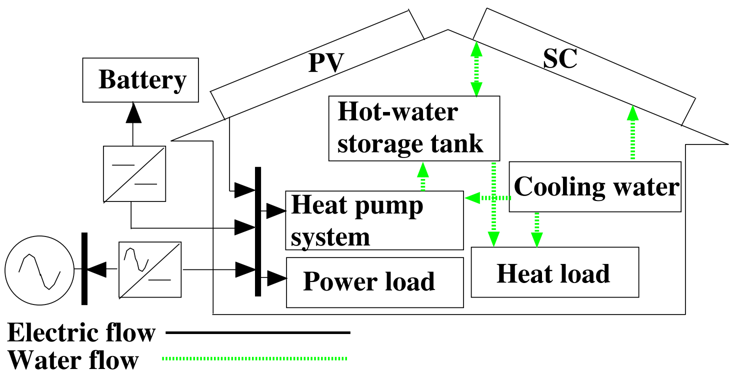


Table 1. System capacities (Size of general-purpose model in Japan).

Equipments	Capacities
Rated power output of PV	3.5 kW
Rated output of heat pump system	4.5 kW/1.5 kW
Hot-water storage tank	370 L
Total Storage battery capacity (lithium-ion type)	25 kWh
Inverter capacity (bi-directional type)	6 kW

2.1. PV Power Output

A lot of PV power outputs are determined by some parameters. This research assumes that η_{PV}, n_{PV} and S_{PV} have a conversion efficiency of PV = 14.4%, the temperature of the cell t_{CR} is 25 °C, the number of PV panels is 18, and the total area of a PV is 1.3 m^2, respectively [13]. At a weather condition with solar radiation I_{in} [kW/m^2] and temperature of cell t_{CR}, the power output of PV P_{PV} [kW] is determined by the following equation [14].

$$P_{PV} = \eta_{PV} n_{PV} S_{PV} I_{in} (1 - 0.005(t_{CR} - 25)) \tag{1}$$

In this research, it is assumed that the temperature of cell t_{CR} is equal to the air temperature.

2.2. Solar Collector

This research assumes that η_{SC} = 60%, n_{SC} = 3 and S_{SC} = 1.6 m^2 are heat collection efficiency of SC, the number of SC panels and total area of a SC, respectively. The heat collection of SC Q_{SC}[J] at a weather condition with solar radiation I_{sc} [W/m^2] is determined by following equation [15].

$$Q_{SC} = \eta_{SC} \cdot n_{SC} \cdot S_{SC} \cdot I_{sc} \tag{2}$$

Although η_{SC} is changed by differences of weather or temperature, this paper assumes that η_{SC} is constant. In actual operation, available heat collection will be used for optimal operation. The amount of water in the hot-water storage tank W = 370 L is the parameter of the electric water heater. Variation in temperature about the inlet temperature of the hot-water storage tank is represented by the following equations [16].

$$Q_{SC} + Q_{tl} + Q_{sw} - Q_{loss} = \beta \cdot A_w \frac{dT_h}{dt} \tag{3}$$

$$Q_h = \beta \cdot A_w \cdot T_h \tag{4}$$

$$Q_{loss} = -\alpha_h (T_h - T) \tag{5}$$

In the above equations, T_h [°C] is the inlet temperature of the hot-water storage tank, Q_h [J] is the amount of heat in the hot-water storage tank, β [J/(L °C)] is the volumetric specific heat of water (=4.184 J/(L °C)), A_w [L] is capacity of hot-water storage tank, α_h is the heat loss coefficient (=0.0060209 W/°C), T [°C] is air temperature and Q_{loss} [W] is the amount of heat loss generated by hot-water storage tank. The flow rate of hot water A_{tl} [L/s] is equal to the flow rate of water A_{sw} [L/s]. The amount of heat requirement Q_{tl} [W] and amount of heat generated by water Q_{sw} [W] are represented by the following equations.

$$Q_{tl} = \beta \cdot A_{tl} (T_{hw} - T_h) \tag{6}$$

$$Q_{sw} = \beta \cdot A_{sw} (T_w - T_h) \tag{7}$$

In the above equations, T_{hw} [°C], T_w [°C] and T_h [°C] are the temperature of hot water, temperature of cooling water and inlet temperature of hot-water storage tank, respectively. The amount of heat generated by the heat pump system Q_{HP} [J] is represented by the temperature generated by the heat pump system T_e [°C] as shown in the following equation.

$$Q_{HP} = \beta \cdot A_{tl}(T_e - T_h) \tag{8}$$

The power consumption of heat pump system P_{HP} [kWh] is represented by following equation.

$$P_{HP} = \frac{Q_{HP}}{\eta_{HP} H_a} \tag{9}$$

In above equation, H_a (=3.6 MJ/kWh) is the ratio by value from P_{HP} to Q_{HP}, and η_{HP} (4.5 kW/1.5 kW) is the rated output of the heat pump system, respectively.

3. Optimization Method

In simulation of this research, Tabu Search (TS) is used for optimal operation of DC smart house. TS was proposed in 1986 by Glover. More details about TS can be found in [17,18]. Minimization of the operational cost for the DC smart house is the goal of this research. Therefore, the objective function is assumed to be the operational cost in this simulation. The objective function is minimized at each time point, so the obtained solutions are assumed to be the hourly amount of charge/discharge of the battery. The objective function and constraint condition for simulation are as follows.

Objective function:

$$C_{day} = \sum_{i=1}^{24} (P_{BUYi} - P_{SALEi}) C_{pi} \tag{10}$$

$$P_{BUYi} = \eta_{inv}(P_{PLi} + P_{HPi} + \eta_{bat} P_{DCi}) \tag{11}$$

$$P_{SALEi} = \begin{cases} \eta_{inv}(P_{PVi} + \eta_{bat} P_{DCi} - P_{PLi} - P_{HPi}) \\ (P_{DC} \leq 0) \\ \eta_{inv}(P_{PVi} - \eta_{bat} P_{DCi} - P_{PLi} - P_{HPi}) \\ (P_{DC} > 0) \end{cases} \tag{12}$$

In the above objective function, C_{day} [YEN] is the operational cost per day, C_p is electric power rate. This is equal to 11.46 YEN/kWh at nighttime (23:00–07:00), 26.22 YEN/kWh during living hours (07:00–10:00 and 17:00–23:00), and 35.04 YEN/kWh during daytime hours (10:00–17:00) [19]. P_{BUY} [kWh] is purchasing electric power consumption, P_{SALE} [kWh] is selling electric power, P_{PL} [kWh] is power consumption of load, P_{HP} [kWh] is power consumption of heat pump system, P_{DC} [kWh] is charge/discharge power of battery. According to feed-in-tariffs for PV systems in Japan, the selling electric power rate is set to 39 YEN/kWh in this paper. If P_{DC} is positive, the battery will charge electric power.

Constraint condition:

$$20\% \le \eta_{C_B} \le 100\% \tag{13}$$

$$\eta_{C_B} = \frac{C_B}{C_{Bmax}} \times 100 \tag{14}$$

$$|P_I| \le 6\ \mathrm{kW} \tag{15}$$

$$P_{BUYi-1} \times 0.8 \le P_{BUYi} \le P_{BUYi-1} \times 1.2 \tag{16}$$

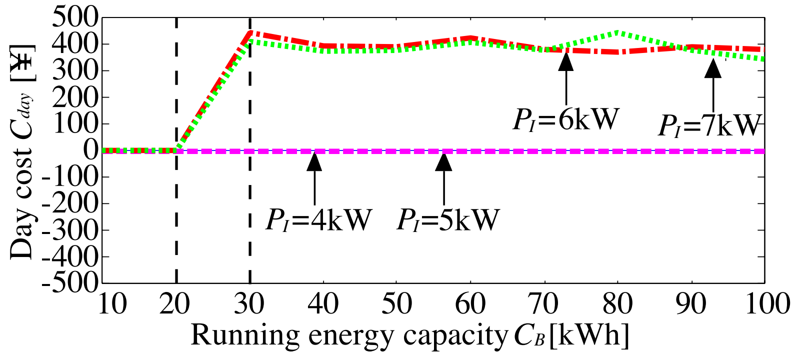
$$P_{SALEi-1} \times 0.8 \le P_{SALEi} \le P_{SALEi-1} \times 1.2 \tag{17}$$

In the above constraint conditions, C_B [kWh] is the total charge/discharge power of battery , P_I is the inverter capacity (=6 kW). This approach aims to obtain more benefit for electrical power selling and to smooth the fluctuating power output of PV. Additionally, the optimal reference fixes the combination output of PV and battery to be constant from 10:00 to 17:00 in order for the power fluctuation in the grid point to be stable.

4. Determination of Battery Capacity

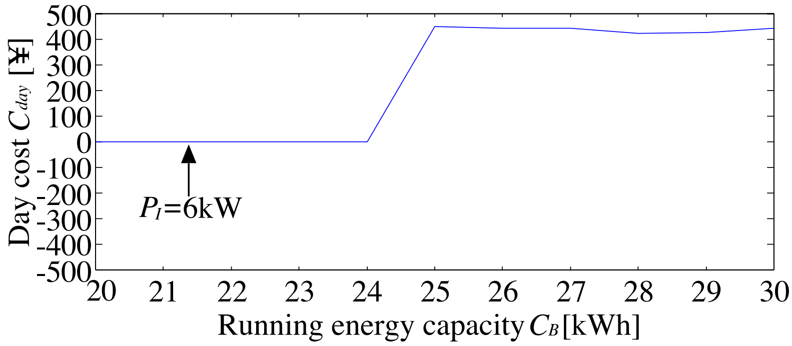
The advantages of the installed battery is a smooth power output and the ability to provide the required power supply to the load on a cloudy or rainy day. However, it is better to reduce the capital cost of the battery. Therefore, optimal capacities of the battery and inverter are determined by simulation results in this research. In this simulation, it is assumed that I_{in} = 0 kW/m^2. Additionally, customers will use hot water for 3 h (three persons) per day. In Figure 2, the vertical axis indicates operational cost per day C_{day}, and the horizontal axis indicates the capacity of the battery C_{Bx}. According to inverter capacity P_I described in Figure 2, the case of C_{day} = 0 is not satisfied with the constraint condition. Similar results are found in Figure 2b. Therefore, Figure 2 shows that the optimal combination is P_{Iopt} = 6 kW and C_{Bopt} = 25 kWh.

Figure 2. Optimal dimension of storage battery. (**a**) 10 kWh–100 kWh; (**b**) 20 kWh–30 kWh.



(**a**)

Figure 2. *Cont.*



(**b**)

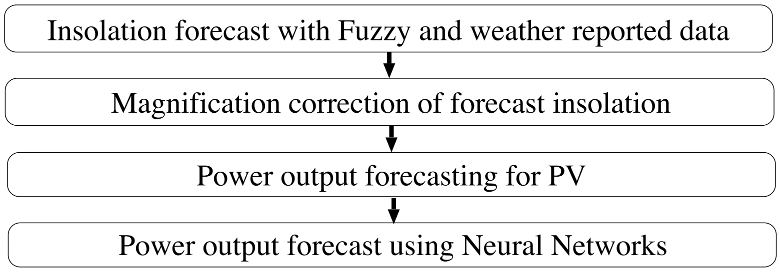
5. PV Power Output Forecasting

The authors proposed the power output forecasting technique of PV system based on hourly solar radiation forecasting one day ahead by using weather reported data, Fuzzy theory and Recurrent Neural Network (RNN) [8], as shown in Figure 3. This chapter shows the summary of the PV power output forecasting method. Since the detailed value of solar radiation prediction is not reported by the Meteorological Agency, the Fuzzy theory is adopted to determine the hourly solar radiation by using weather reported data such as humidity and cloud cover. This technique also includes the correction method for annual solar radiation forecast errors. Additionally, since the power output of the PV system fluctuates depending on weather conditions, the training process of NN tends to be unstable. However, Recurrent NN (RNN) is known to be a good tool for time-series data forecasting. The RNN has l = 24 and m = 1–30 neurons in the input layer and hidden layer, and n = 24 neurons in the output layer. These neurons are connected with linear coupling, and x_1–x_l are input data to RNN. Input data x_1–x_l (24 h × 30 days) for the training dataset are determined by Fuzzy theory. There are connection weights between each neuron. The output of hidden layer neurons are converted to nonlinear values by hyperbolic tangent sigmoid-function. RNN has a context layer. This layer contains a copy of the hidden layer with time-delay lines, and added as feedback structure [20]. The context layer reflects both the input and output layer's information to the structure of RNN. In this research, information of one time-step lag from the output units is used in the context layer. After each output unit provides the information relating to one time-step interval, the training of the network becomes stable. Based on conventional research [21], the authors think that it is convenient to make the forecast model by a trial-and-error approach. As a consequence, the past information is maintained to RNN with the progress of learning. The proposed technique for the application of RNN is trained by power output data based on Fuzzy theory and weather reported data. Because the Fuzzy model determines the solar radiation forecast data, RNN will train the power output smoothly.

6. Simulation

This section shows the simulation conditions, simulation results and the comparisons for three cases.

Figure 3. Forecasting method.



6.1. Simulation Conditions

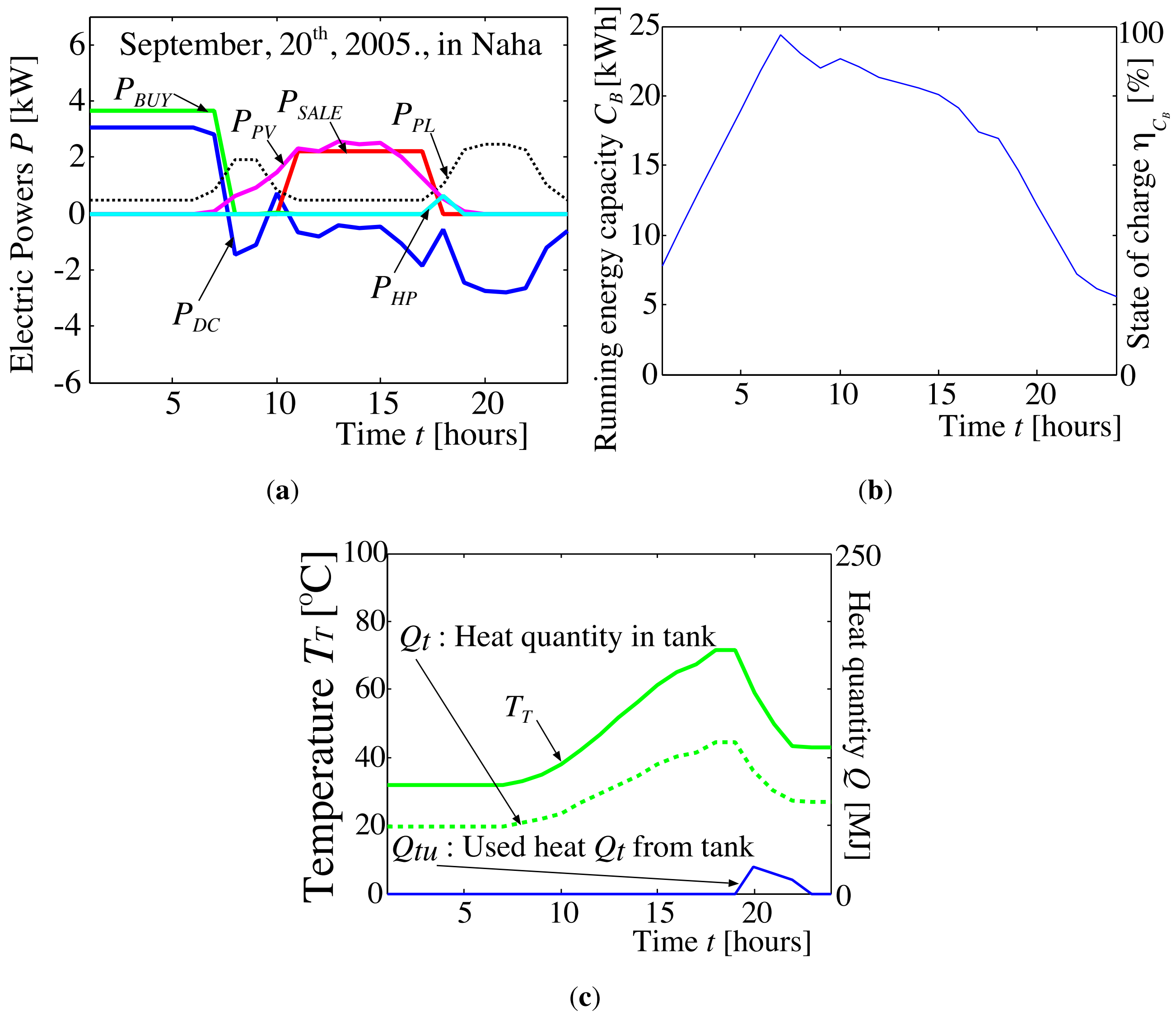
The authors assume three cases for this simulation, case 1: No forecast errors, case 2: Forecast hourly time, case 3: Re-planning for a sunny day and a rainy day. In addition, customers of the DC smart house will use hot water for 3 h (three persons) per day. Here, we assume that one person will use 100 L hot water from the storage tank between 19:00 and 22:00. At 19:00, if T_T of the inlet temperature in the hot-water storage tank falls much below 60 °C, the water in the hot-water storage tank will be increased by a heat pump system in advance at night. The hourly weather reported data is delivered over 24 h at 4 time points (0:00, 6:00, 12:00, 18:00) on 1 day. In this simulation, the assumption of no forecast errors is case 1. The re-planning operation at 06:00 for initial time on one day is assumed to be case 2. The re-planning operation, case 3, is modified at the time of updating weather reported data for 4 times on 1 day. The validity of the proposed method is confirmed by compared with the case of no forecast errors using weather data in Okinawa, Japan, 2005, on sunny and rainy day simulations [22]. This paper focuses on optimizing re-planning operation applying solar radiation forecasting in one day for an existing smart house. Considering other cases, such as yearly weather data, will be another focus of research in the future. If we consider the statistical yearly weather data, the issue includes the optimizing system capacities of the smart house.

6.2. Simulation Results and Discussions

The simulation results on a sunny day of case 1 and 3 are shown in Figures 4 and 5. Figures 4a and 5a show the electric power [kW] on the time axis. In these Figures, P_{DC} [kW] indicates the charge/discharge power of battery determined by TS. If P_{DC} is positive, the battery will charge electric power. P_{PV} [kW] is the power output of PV, P_{PL} [kWh] is the power consumption of load, P_{HP} [kWh] is the power consumption of the heat pump system, P_{BUY} [kWh] is the purchasing electric power consumption, P_{SALE} [kWh] is selling electric power. Figures 4b and 5b show the running energy capacity of battery C_B [kWh], and state of charge η_{CB} [%].

In Figures 4c and 5c, the left side vertical axis indicates the inlet temperature of hot-water storage tank T_T [°C], the right side vertical axis indicates the heat quantity Q [MJ], and the horizontal axis indicates hour. In these Figures, Q_t [MJ] is heat quantity in tank, Q_{tu} [MJ] is used heat quantity from tank. As shown in Figures 4 and 5, all simulation results are satisfied with constraint conditions as described in Section 3.

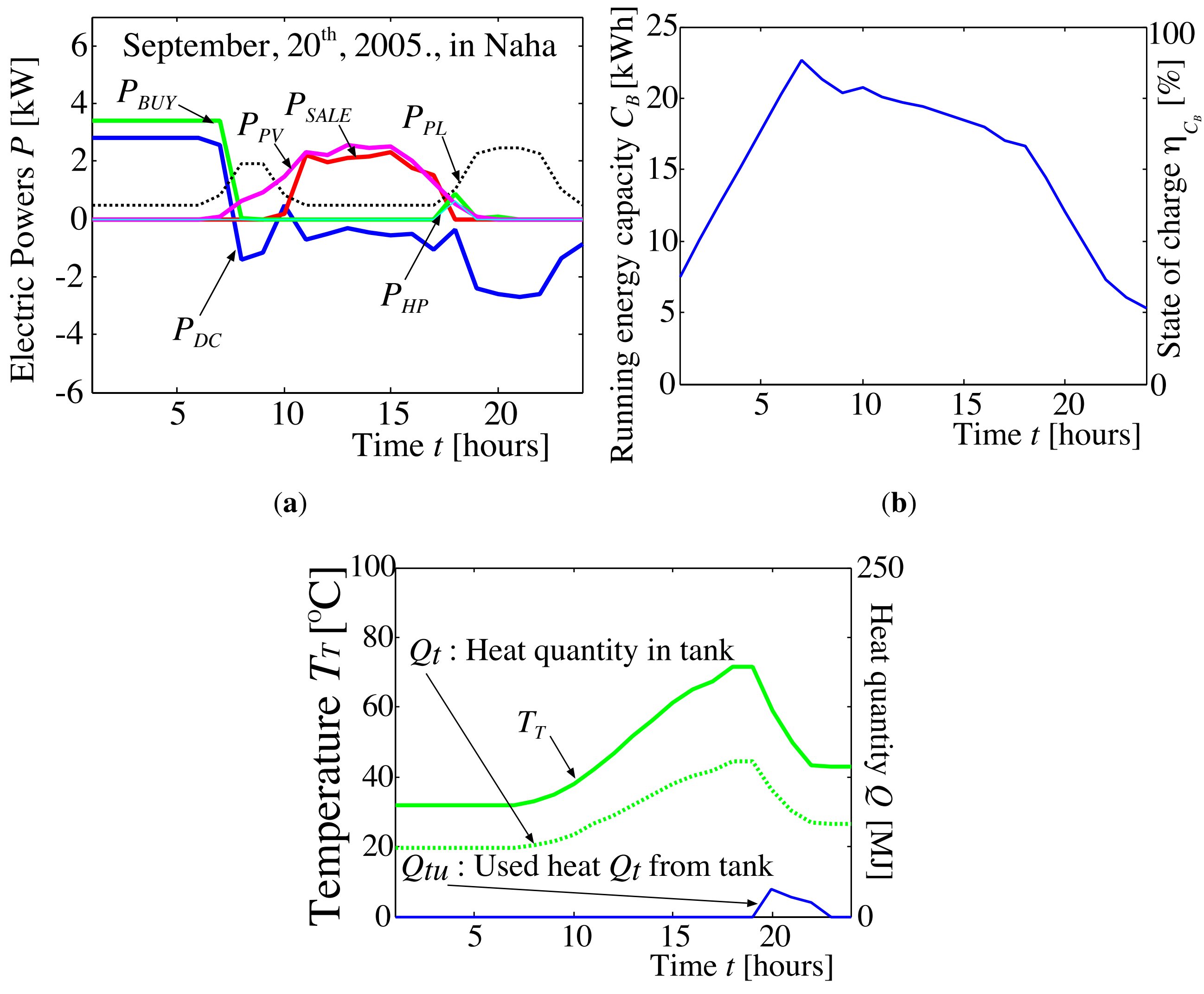
Figure 4. Simulation results (sunny day, case 1: no forecast errors). (**a**) Optimized result; (**b**) Battery; (**c**) Temperature of tank and used heat quantity.



It is also confirmed by comparing the Figures 4 and 5, that the result of the proposed re-planning operation in case 3 is similar to case 1. Additionally, the battery charges the electric power at night time at an inexpensive electric rate, and provides the charged power to the heat pump system in a sunless period (19:00).

More detail regarding simulation results about rainy days is beyond the scope of this research. However, Table 2 shows the calculation results of operational cost, electric power selling, electric power buying, generated electric power, electric power load, heat load, electric power loss and forecast errors for all cases on a rainy day. The lower line in Table 2 represents the mean absolute value (and the percentage values) for solar radiation forecast errors. The percentage values of solar radiation forecast errors are calculated by dividing the total errors by total solar radiation for 1 day. Table 3 shows the calculation results of operational cost for all cases on a sunny day. These simulation results show that the daily operational cost is minimized by the proposed method on two solar radiation patterns. This also means that the benefit of the installed battery is confirmed by these results.

Figure 5. Simulation results (sunny day, case 3: re-planning operation). (**a**) Optimized result; (**b**) Battery; (**c**) Temperature of tank and used heat quantity.



(**a**) (**b**)

(**c**)

The calculation results of cases 1–3 are similar to the simulation results as described in Figures 4 and 5. It should be noted that weather varies with the seasons. To understand more about simulation results, Table 4 represents the mean generated electric power of PV, absolute values of forecast errors and the percentages every month in 2005. It can be confirmed that case 3 is proposed to be superior to case 2. Whereas the simulation results of operational cost for case 3 are very similar to case 1, the results of electric power loss are higher even than case 2. This reason for this is clear because the objective function in this research is to minimize the operational cost, as described in Section 3. So, if we change the objective function, the simulation results will be different. Otherwise, the difference of the operation time between cases 2 and 3 causes the electric power loss due to the charge/discharge electric power of battery. Therefore, considering further research that is not explored in this article, our future research will mainly focus on (1) Applying a new strategy for compensating electric power loss and forecast errors; (2) Optimizing the system capacities of a DC smart house; and (3) Applying new and advanced artificial intelligence techniques for optimal operation.

Table 2. Running cost (rainy day).

Each case	case 1	case 2	case 3
Operational cost [YEN/day]	329.90	392.36	344.28
Electric power selling [kWh/day]	0.68	1.40	0.88
Electric power buying [kWh/day]	30.66	31.05	31.73
Generated electric power [kWh/day]	2.66	2.66	2.66
Electric power load [kWh/day]	24.04	24.04	24.04
Heat load [kWh/day]	4.85	4.65	4.83
Electric power loss [kWh/day]	3.75	3.62	4.64
Forecast errors [kWh/day]	—	1.18	0.77
Percentages of forecast errors		(44.3%)	(29.1%)

Table 3. Running cost (sunny day).

Each case	case 1	case 2	case 3
Operational cost [YEN/day]	–291.85	–252.62	–271.61
Electric power selling [kWh/day]	15.48	14.30	15.51
Electric power buying [kWh/day]	26.35	24.75	27.19
Generated electric power [kWh/day]	19.20	19.20	19.20
Electric power load [kWh/day]	24.04	24.04	24.04
Heat load [kWh/day]	0.62	0.62	0.62
Electric power loss [kWh/day]	5.41	4.99	6.22
Forecast errors [kWh/day]	—	4.36	2.61
Percentages of forecast errors		(22.7%)	(13.6%)

Table 4. Mean generated electric power of PV and forecast errors at Naha in 2005.

Month	**1**	**2**	**3**	**4**	**5**	**6**
Mean generated electric power [kWh/day]	8.08	7.33	12.76	16.02	15.26	15.02
Mean forecast errors [kWh/day] (case 2)	2.96	2.97	3.68	3.99	4.45	4.45
Percentages of forecast errors [%] (case 2)	36.60	40.50	28.88	24.93	29.17	29.62
Mean forecast errors [kWh/day] (case 3)	2.00	1.47	1.03	1.59	1.67	1.43
Percentages of forecast errors [%] (case 3)	24.79	20.08	8.06	9.90	10.91	9.50
Month	**7**	**8**	**9**	**10**	**11**	**12**
Mean generated electric power [kWh/day]	21.58	18.51	17.55	15.02	10.85	8.62
Mean forecast errors [kWh/day] (case 2)	4.78	4.82	4.53	3.89	3.50	2.81
Percentages of forecast errors [%] (case 2)	22.16	26.03	25.81	25.90	32.28	32.61
Mean forecast errors [kWh/day] (case 3)	1.19	1.65	2.27	1.77	1.51	1.15
Percentages of forecast errors [%] (case 3)	5.54	8.94	12.94	11.76	13.89	13.39

7. Conclusions

This paper proposes the re-planning operation method using Tabu Search for a DC smart house including PV, SC, battery, and a heat pump system. The proposed method is based on the solar radiation forecasting method using weather reported data collection, Fuzzy theory and Recurrent Neural Network. Additionally, the re-planning operation method was used to consider solar radiation forecast error, battery and inverter losses. Simulation results show that daily running costs are minimized by the proposed method on two solar radiation patterns. The validity of the proposed re-planning method is confirmed by comparing the case of no forecast errors. The simulation results show that, if it is possible to provide power load and heat load by PV with SC, the advantage to the consumer will increase.

Author Contributions

Modeling of the DC smart house and the optimization method were performed by Atsushi Yona and Tomonobu Senjyu. Data analysis was done by Atsushi Yona. Manuscript was written by Atsushi Yona, Tomonobu Senjyu and Paras Mandal. Toshihisa Funabashi, Paras Mandal and Chul-Hwan Kim took part in the technical task on forecasting method.

Conflicts of Interest

The authors declare no conflict of interest.

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