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Optimal Adjustment Strategy for Operating Schedule of Energy System under Uncertainty of Renewable Sources and Demand Changes

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Abstract

Recently, batteries and thermal energy storage (TES) technologies have become increasingly important for reducing operating costs. Although there have been many previous studies to optimise the operating schedule of energy systems, they only considered perfect predictions for demand and photovoltaic (PV) power generation, implying that these predicted values did not change at the operating time. In addition, some studies that considered the uncertainty proposed complex methods to measure or forecast the effect of each contributing factor, such as outdoor temperatures and solar radiation with an objective function. Therefore, a practical method that can specify a real-time control for each component under this uncertainty is strongly needed. In this study, we propose a new optimisation strategy to handle the uncertainty and call it the “two-time steps recalculation strategy” (TtsR). The results show that TtsR requires lower computational time than “all time steps recalculation strategy” (AtsR) to obtain a quasi-optimal solution when there were unpredicted changes in power generation and demand; meanwhile, TtsR was able to maintain computational accuracy.

Keywords – uncertainty; optimisation; photovoltaics; energy storage

1. Introduction

In recent years, energy management systems (EMS) that can operate important facility equipment have been attracting a great deal of attention. This technology can reduce energy consumption rates, operating costs, and CO₂ emissions. Several EMS technologies have been used successfully in homes (HEMSs), buildings (BEMSs), and factories (FEMSs) [1,2]. Some previous studies aimed to determine the optimal operating schedules for EMSs. In terms of mathematical optimisation techniques, mixed-integer linear programming (MILP) methods have been often used to minimise the operating costs. Ashouri et al. [3] used MILP to minimise annual operating costs of a large-scale energy system. Buoro et al. [4] also applied MILP to

optimise the sizing and operating schedule of a distributed cogeneration system that employed solar district heating. However, because common heat source machines and pumps have nonlinear configurations, modern energy system modelling also needs highly nonlinear characteristics. In addition, MILP cannot handle iterative calculations such as determining water temperature.

For complex nonlinear problems, some studies have used stochastic methods (e.g. genetic algorithms) for optimisation of energy system operations. However, these studies only considered perfect prediction models and did not consider the uncertainty of power generation from renewable energy resources and demand changes caused by occupant behaviour.

A simple and effective method to recalculate operating schedules of all time steps at every time interval is referred to as the “all time steps recalculation strategy” (AtsR) in this paper. The AtsR can be thought of as an ideal optimisation strategy, but it is expected to require large amounts of computation time. Thus, it cannot be easily applied to actual energy management systems, although computation speed is also significant. In this paper, we propose a new recalculation strategy called the “two time steps recalculation strategy” (TtsR). The TtsR aims to recalculate operating schedules over two time steps: from the current time step and next time step. We compared TtsR and AtsR procedures and results in order to clarify the effectiveness of the new TtsR.

2. Materials

2.1 Demand profile and electricity price

We considered an office building in Tokyo with a total floor space of 20,000 m². The study took place over a 24 h period with 1 h intervals. Electricity demand, which represented electricity consumption for lighting and PCs, was determined using the specific statistical data [5]. The experiment day represented a typical day in August.

The price of purchased electricity in each time interval could change with the total hourly predicted electricity consumption. Electricity and cooling demands, and the sold and purchased price of electricity, are shown in **Fig. 1**. In this paper, these demand curves were set as predicted demands. When we considered unpredicted changes in the demand and solar radiation, we applied random numbers to these demands to create new values for them.

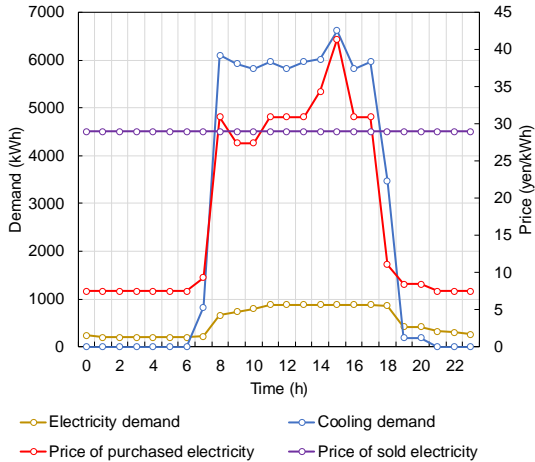


Fig. 1. Electricity and cooling demands, and electricity prices.

2.2 Energy system

We used an energy system that included a battery, PV device, power conditioner, two centrifugal refrigerators (CR1 and CR2), three air-source heat pumps (AHP1, AHP2, and AHP3), and TES for cooling. A schematic diagram of the system is shown in **Fig. 2**.

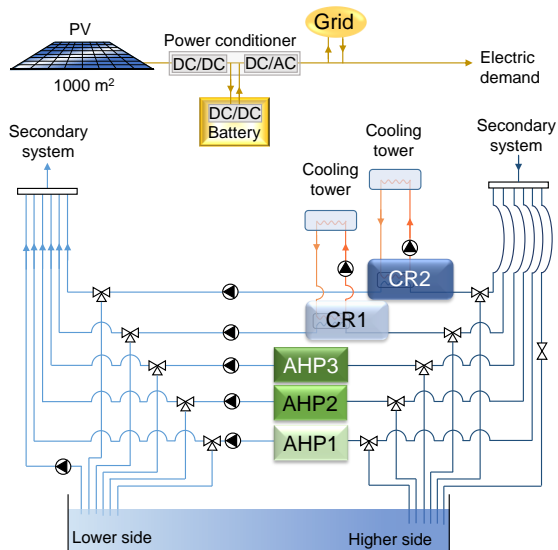


Fig. 2. Schematic diagram of the energy system.

In terms of an electric system, the area of the PV panels and conversion rate were set to 1000 m² and 13%, respectively. The efficiency of the power conditioning system was 97%. The capacity and maximum amount of charging or discharging of the battery were set to 1500 kWh and 300 kW, respectively.

In terms of the HVAC system, the capacity of the TES was 10,000 kWh. The charging or discharging efficiency was 100%, and the self-heat loss rate was set to 0.2%/h. The heat source equipment consisted of the five previously mentioned devices, with the rated capacities of CR1 and CR2 set to 2000 kW and 1500 kW, respectively; those of AHP1, AHP2, and AHP3 were set to 1200 kW, 1000 kW, and 600 kW, respectively. The rated COPs of CR and AHP based on primary energy were 2.04 and 1.3, respectively. The characteristics of each device including the cooling towers (only CR1 and CR2) and pumps were modelled according to the nonlinear configuration described in Ref. [6].

3. Optimisation Method

3.1 Problem formulation

In this paper, the aim of the optimisation was to minimise the operating costs for a 24-h operation period, and this is expressed as the following equation:

$$\min f = \sum_{t=1}^{TimeH} \{Price_p^t \times (ec_{elec}^t + ec_{HVAC}^t) - Price_s^t \times (PVtoG^t)\} \quad (1)$$

where t denotes the time step (h), $TimeH$ represents the time horizon (24 h), $Price_p^t$ is the price of purchased electricity (yen/kWh), $Price_s^t$ indicates the price of sold electricity (yen/kWh), ec_{elec}^t is the energy consumption of the electric system per hour (kWh) and ec_{HVAC}^t denotes the energy consumption of an HVAC system that includes CRs, AHPs, pumps, and cooling towers. In addition, $ato\beta^t$, as in $PVtoG^t$, signifies the amount of electricity or cooling heat transferred from device α to device β (kWh). The number of decision variables for this study was 240 (10 types \times 24 h), and the number of constraints was 168.

3.2 Optimisation method

We applied the epsilon constrained differential evolution (ϵ DE) developed by Takahama and Sakai [7] in order to find the quasi-optimal solution effectively under constraint conditions. ϵ DE is a hybrid method based on the original DE [8] and epsilon constraint handling methods. The original DE, which belongs to the field of artificial intelligence, does not

take into account the constraints, except for the boundary constraints. Although there are several constraint handling methods, ε DE can obtain a more accurate quasi-optimal solution quickly according to the results of Mallipeddi et al. [9]. In addition, ε DE can solve many optimisation problems, regardless of the search domain's landscape, such as linear, nonlinear, convex, concave, discrete, and continuous modelling problems.

$$\varphi(x_i) = \sum_k \max\{0, g_k(x_i)\}^p + \sum_k |h_k(x_i)|^p \quad (9)$$

$$(f_1, \varphi_1) <_{\varepsilon} \begin{cases} f_1 < f_2, & \text{if } \varphi_1, \varphi_2 \leq \varepsilon \\ f_1 < f_2, & \text{if } \varphi_1 = \varphi_2 \\ \varphi_1 < \varphi_2, & \text{otherwise} \end{cases} \quad (10)$$

3.2 Proposed methodology

Unpredicted changes in power generation from PV devices can occur when weather conditions change. Moreover, unpredicted changes in the electricity or cooling demand can be caused by changes in occupant behaviours. When those changes occur, operations must be rescheduled to match the balance between demand and supply and minimise operating costs. In order to minimise the objective function value, the best strategy is to recalculate for all time steps under the changed conditions, as shown in **Fig. 3**. The horizontal axis represents the recalculated time horizon, and the vertical axis indicates the time of recalculation. For example, three time intervals (9, 10, 11 p.m.) were recalculated at 9 p.m. Generally, long computation times are required to optimise a complex nonlinear problem with mathematical techniques. However, ε DE can be used to obtain the quasi-optimal solution stochastically over short computation times. Thus, ε DE was applied to the AtsR strategy.

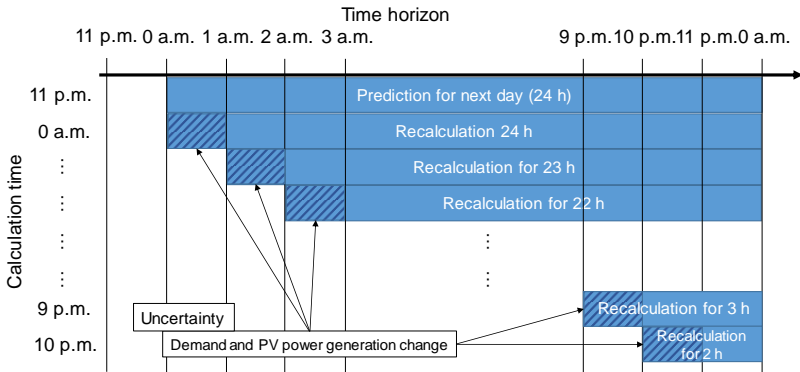


Fig. 3. Recalculation concept of AtsR.

Because AtsR recalculates at every time step, this strategy yields an accurate quasi-optimal solution. However, this requires long computation times, especially for former calculation times that are associated with long time horizon recalculations. Thus, this technique is not always practical to use with actual systems. Here, we propose a new recalculation strategy, TtsR. We recalculated the operating schedules to match the energy balance for 2 h during the current time interval (t) and again for the next time interval ($t + 1$), as shown in **Fig. 4**.

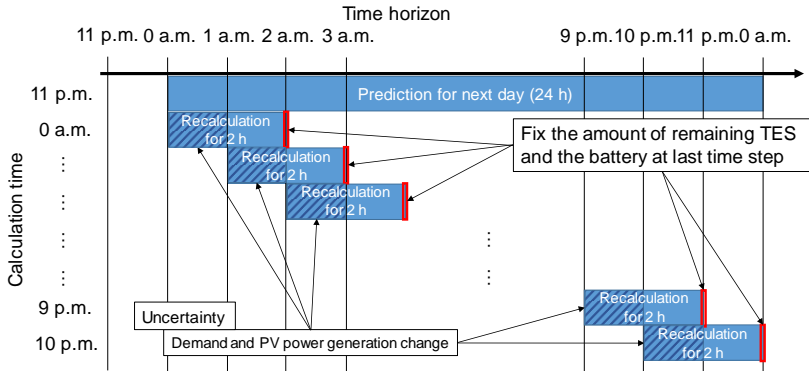


Fig. 4. Recalculation concept of TtsR.

4. Results and Discussion

4.1. Case study

We conducted three case studies in order to clarify the accuracy and effectiveness of the proposed TtsR against AtsR. Case 1 served as the perfect prediction, Case 2 represented demand changes, and Case 3 represented PV power generation and demand changes simultaneously. The power generation from the PV device was changed by a uniform random number in the range of the upper and lower 20%, as shown in **Fig. 5**. In this figure, the blue bars (predicted PV) indicate the amount of power generated from the PV device during the prediction, and the red bars (changed PV) indicate the amount of power generated after modelling the uncertainty. The power level increased by 19.2% at 1 p.m. and decreased by 12–14% at 9 a.m., 10 a.m., and 2 p.m. in Case 1. In the results for the uncertainty modelling, the total amount of power generation increased from 773.4 kWh/day (predicted PV) to 781.2 kWh/day (changed PV).

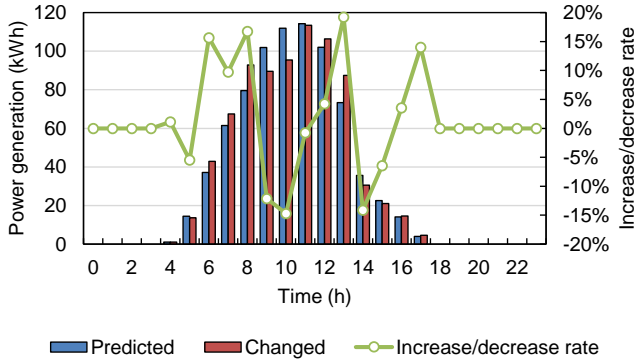
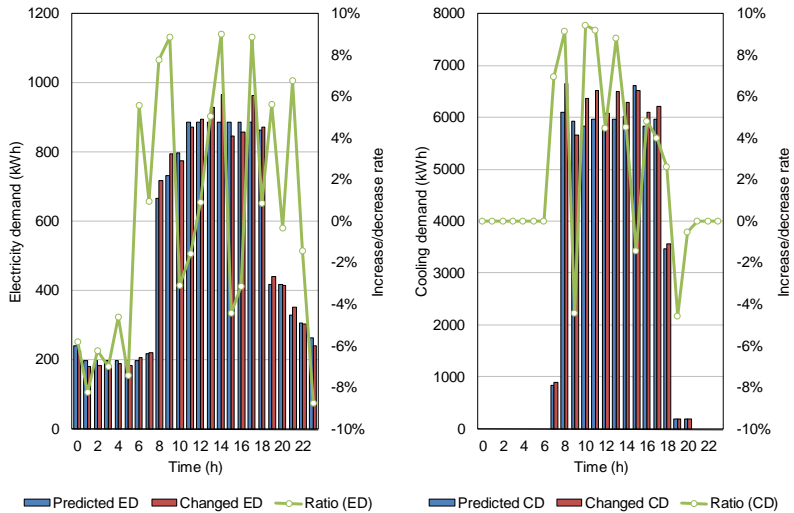


Fig. 5. PV power generation variation.

We also used a model that accounted for the uncertainty of demand resulting from changes in occupant behaviours. The demand changes were modelled by using a uniform random number in the range of the upper and lower 10%. Electricity demand and cooling demand changed as shown in **Figs. 6(a)** and **(b)**, respectively. The results show that the total amount of electricity demand increased from 12,614 kWh/day to 12,794 kWh/day, while the cooling demand increased from 64,715 kWh/day to 67,736 kWh/day.



(a) Electricity demand

(b) Cooling demand

Fig. 6. Variation of unpredicted changes

4.2. Results

In order to confirm how the operating schedule changed using the TtsR method, the quasi-optimal operations at 1 p.m. for Case 1 and Case 2-2 (TtsR) are shown in **Fig. 7**. Here, it was supposed that the cooling demand increased unexpectedly by 8.8% compared to the predicted amount. Although the amount of thermal energy discharged from TES to the demand was zero in Case 1, TES discharged some thermal energy (263 kWh) to the cooling demand in Case 2-2. The reason for this was that the total capacity of each piece of machinery was lower than the increased demand (6500 kWh). However, the amount of discharged thermal energy from the TES was lower than the original amount of that at 2 p.m. in order to maintain the amount of remaining TES at the end of the 2 p.m. interval. In order to meet the demand, AHP2 and AHP3 generated more heat from cooling than in Case 1.

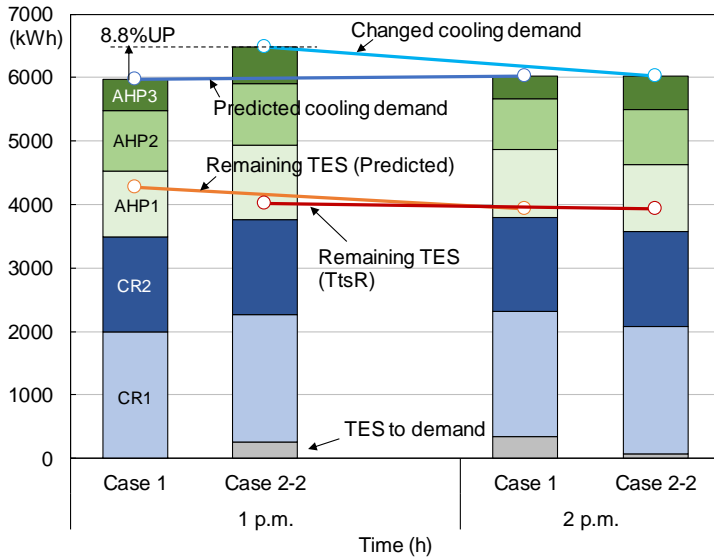


Fig. 7. Comparison of each solution for Case 1 and Case 3-2.

The results for Case 3-1 (AtsR) and Case 3-2 (TtsR), which considered both types of uncertainty, are shown in **Fig. 8**. The total operating costs for Case 3-1 and Case 3-2 were 636,536 yen/day and 641,087 yen/day, respectively. There was no detection of any major differences in operating costs (i.e., the cost increase was less than 0.7%). The computation times of Case 3-1 and Case 3-2 were 4521 s and 1234 s, respectively. Thus, TtsR

reduced the computation time by 73%. In general, we found that TtsR performed well in dealing with common types of uncertainty while maintaining the computational accuracy for actual building scenarios.

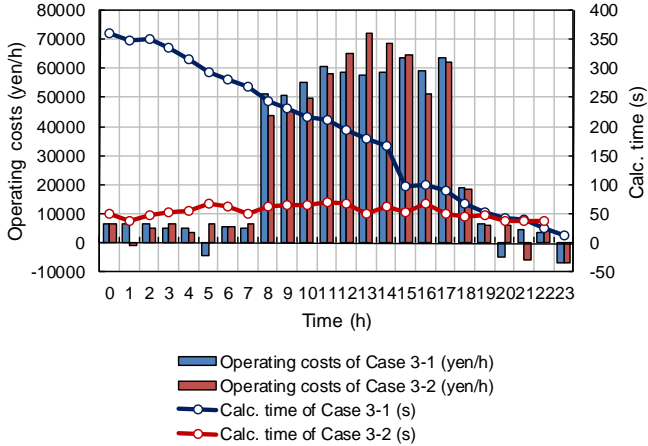


Fig. 8. Comparison of Case 3-1 and Case 3-2.

5. Conclusion

In this paper, we propose a new strategy, TtsR, for recalculating the operating schedules of EMSs in order to optimise energy production and minimise costs during periods of uncertainty resulting from changes in renewable energy sources and changes in demand initiated by alterations in occupant behaviour. These unpredicted changes are often encountered during the operation of actual energy systems. In TtsR, the operating schedules of two time steps were optimised while fixing the amount of remaining battery power and TES at the second time step. We compared TtsR with AtsR, which optimises the operating schedules of all time steps and while it is highly accurate it is a more time consuming procedure. Comparisons of the two calculation strategies showed that TtsR could obtain the quasi-optimal solution in 73% shorter computation times than AtsR, while still maintaining good accuracy. Therefore, TtsR should be a valuable technique to use for dealing with uncertainty when optimising energy systems in actual buildings.

Acknowledgement

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