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Prediction model and control method for realizing demand response

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Abstract

Demand response, which aims to stabilize power supply and cost of electricity, has garnered considerable research interest in recent years. It is expected to be particularly useful in small- and medium-sized office buildings, which are responsible for a large share of the total electricity consumption of an area. In this paper, we propose a method for creating a prediction model and control method for realizing demand response, and report its evaluation results.

Keywords: Demand response, Air-conditioning, Building power demand forecast model, Energy saving control

1. Introduction

Distributed energy systems that use demand-side resources are in high demand in Japan [1]. Following the Great East Japan Earthquake that occurred on March 11, 2011, many power plants were closed, which led to a serious power shortage [2]. Demand response (DR) was developed for utilizing demand-side resources and helping consumers save electricity in accordance with the needs of their power companies. A typical DR is shown in Fig. 1. To ensure an adequately coordinated power supply through DR, the supply to a significant number of customers should be controlled. It is difficult for power companies to directly control the power consumption of their customers. Therefore, an aggregator is used in DR as an intermediary between the electric power company and the customer, as shown in Fig. 2. Conventionally, DR has been used for peak shift between a large consumer, such as a large factory, and the electric company. However, this limits the target of DR to large consumers, which consequently limits the magnitude of energy reduction. DR is expected to be particularly useful for small- and medium-sized office buildings, which are responsible for a large share of the total electricity consumption.

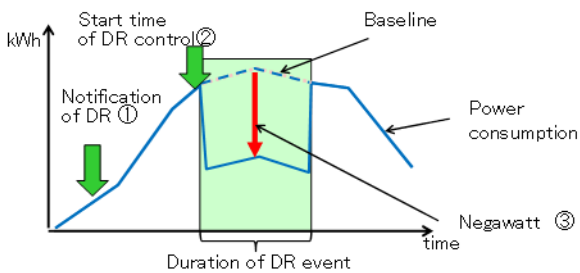

Fig. 1. Overview of demand response.

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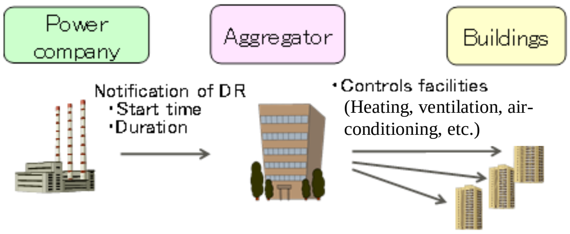


Fig. 2. Role of an aggregator.

We constructed an auto-demand response system in 2015–2016 and conducted a DR demonstration test for small- and medium-sized office buildings [3]. However, it is difficult to select the consumer equipment to be controlled and to determine the control contents in this system. Moreover, such control of the equipment can cause a problem wherein the electricity consumption is not reduced but the consumer comfort is greatly impaired. In this paper, we propose a method for creating a prediction model and control method for realizing DR, and report its evaluation results.

2. Implementing DR in Small and Medium-sized Office Buildings

In this section, we detail our approach to DR. Our proposal comprises three tasks: the construction of a power consumption prediction model for each facility, which considers lighting, air conditioning, and outlets in a building; the determination of energy saving control of each space; and extraction of the optimal control solution.

2.1. Power consumption prediction model for each facility

Statistical and physical models have been researched to predict power consumption. The statistical approach includes the k-nearest neighbors algorithm, multi-regression analysis, and SARIMA [4]. Considerable amount of research has been devoted to predicting the power consumption of buildings using these methods. Ideally, we should calculate the best control contents for a room or a floor, but the calculation for such small units is difficult because an ordinary building measures only its overall consumption of electric power.

Physical models to predict power consumption involve calculating the heating and cooling loads [5]. The energy control system based on the physical model calculates the utilization of energy inputs in a building by this technique. However, it is troublesome to obtain the specifications for a given building and equipment in physical models. Thus, systems based on physical models are challenging to apply to small- and medium-sized office buildings.

Japan has a strong commitment to energy conservation. The cost of measurement of electric power has recently fallen with reduction in the price of necessary equipment. In recent years, it has become possible to construct buildings where electric power supplied for air conditioning, lighting, and office automation equipment can be segregated and the energy consumption measured according to room, floor, and space unit. The factors influencing each type of consumption are different. For instance, lighting equipment is subject to the influence of sunlight, and air conditioning is influenced by the external temperature and the number of people in a given room. A highly precise system can be constructed by separately modeling each type of electric power supply. It then becomes possible to consider the appropriate control that needs to be added to each model. Linear regression is used to make predictions with the models. Linear regression terms can be added together. By adding linear regression equations, it is possible to predict the power consumptions of rooms, floors, and buildings with high accuracy.

2.2. Determination of energy saving control for each space

Various facilities are installed in each floor or room of the building, and their operations as well as that of the system installed for controlling the facilities are different. Therefore, the energy saving control that can be performed during the DR period is different. In addition, even if the same energy saving control is applied to different buildings and floors, the impact on the reduction in the electricity consumption in the area and the consumer comfort also differ. To be productive, DR must control many buildings. It is necessary to be able to generate a control plan for reducing the target electric power using a program that considers the aforementioned differences. To realize this, it is necessary to list energy saving controls that can be implemented in various building facilities, and to be able to select the appropriate control according to the characteristics of the control target area. An explanatory variable of the prediction model equation is used for evaluating the characteristics of each area. Because the prediction model equation is a linear regression equation, a plurality of the prediction models is clustered, facilitating collective control. These are combined as parts of the DR control to enable the achievement of the target power.

2.3. Extraction of optimum control solution

To extract the optimum control solution, the control time of each control pattern was made shorter than the time for DR. This allowed rotating control across buildings and floors. We thus constructed a mechanism to extract and execute a combination of facility controls implemented with minimum environmental impact for a specified amount of reduction in electric power consumption.

We have been conducting research aimed at realizing energy saving in small- to medium-sized office buildings. Further, we studied the power consumption prediction model for each facility using heterogeneous mixture learning technology [6].

3. Energy Saving Control of Air Conditioners Using Heterogeneous Mixture Learning Technique

3.1. Creation of power demand forecast using heterogeneous mixture learning technology

There is no systematic method for data division and selection of explanatory variables for linear model construction. The extraction of appropriate explanatory variables for constructing linear models requires specialized domain knowledge and analytical skills. Therefore, the authors decided to solve this problem by using the heterogeneous mixture learning technology proposed by Mr. Fujimaki. Heterogeneous mixture learning technology can automatically perform data division and extraction of explanatory variables generally performed by experts. This technology requires the periodic execution of three steps based on indicators, as shown in Fig. 3. The three steps—optimization of the data classification conditions (Step 1), optimization of the explanatory variable combinations (Step 2), and deletion of unnecessary prediction models (Step 3)—are referred to as "factorized information amount criteria."

We applied this heterogeneous mixture learning technique to the construction of the power demand model.

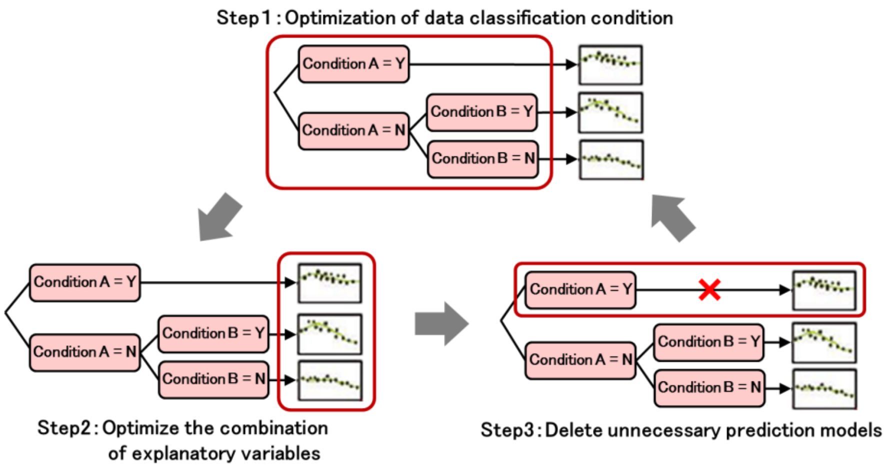


Fig. 3. Overview of heterogeneous mixture learning technology. (Reference [7] 102)

3.2. Target equipment for energy saving control

Air conditioning and lighting equipment were responsible for 72% of the power consumption in the former office building (air conditioning equipment 48%, lighting equipment 24%). However, in recent years, lighting power consumption has drastically decreased by 50%–80% when compared with existing lighting equipment owing to the use of LED lighting. Therefore, the air conditioning equipment has become the target equipment for energy saving control at the time of DR.

There are two points to realize while controlling the DR for an air conditioner.

a. Create a control plan with the power consumption amount as the target value

b. Construct a control system that considers the comfort of the consumers.

A control plan was constructed by using a prediction model of the power consumption, created based on heterogeneous mixture learning technology, to realize “a.”

The cumulative value of the fluctuations in the temperature setting was considered to realize “b.”

4. Summary of the Control System

We explain the operation of the control system in this paragraph. Fig. 4 shows the system configuration. This system is composed of four programs, an EMS (Energy Management System), and an air conditioner. The EMS can change the temperature setting. In addition, it can measure the power consumption and indoor temperature as the trend data. The “modeling program” can estimate the power consumption of the air conditioners on each floor by using the two-year trend data of the EMS. The “prediction program” can load the predictive model and temperature from the weather forecast to calculate the projected power demand for each time period. The “planning program” can create a control plan, which sets a target value. The selection logic of the control plan is as follows.

- From the calculated control plan, extract the planned power usage amount as ±5% of the target value.
- From the extracted plan, select the control plan, which has the smallest change in the temperature range.

During the execution of the control system, the projected power demand is collected from the EMS for a constant period and the difference between the planned value and the actual output is calculated to apply the correction. The “plan execution program” can control the air conditioner using the EMS based on the control plan calculated by the “Prediction program.”

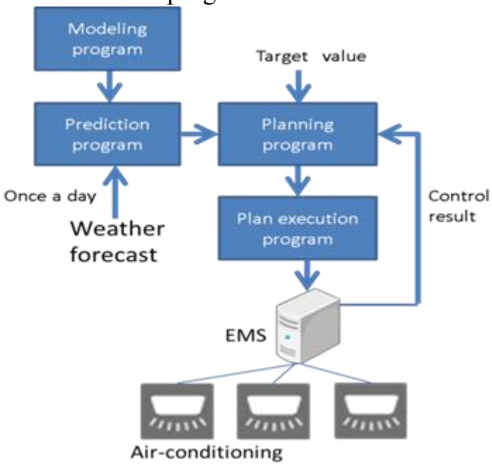


Fig. 4. System configuration.

5. Experiment

We performed an experiment that involved using the control system on the air conditioners in an 8-story building. The experimental conditions are shown in Table 1. The target value was 90% of the predicted value of power consumption when operating all air conditioners at 24 ℃. The range given by ±10% of the target value was the boundary between the success and failure judgment values of the DR control. (This value was adopted from the DR demonstration test conducted mainly by the Ministry of Economy, Trade and Industry in Japan in 2016.)

Table 1. Experimental conditions

Item	Specification
Target	Power consumptions of the 2nd floor, 5th floor, and 6th floor of the 8-story office building
Time and duration of examination	October 1, 2018, 15:00–15:30,16:00–16:30 October 2, 2018, 15:00–15:30,16:00–16:30
DR duration	30 min
Minimum control duration	5 min
Number of control corrections	2 times (10 min and 20 min after start of control)
Other conditions	2nd and 6th floors are huge areas and a part of the 5th floor is the server room, which is not included in the power measurement and control experiment. There are 6 outdoor units and 7 indoor units in the 2nd and 6th floors. There are 5 outdoor units and 5 indoor units in the 5th floor.

5.1. Construction of the power consumption model

We used the EMS data for every hour during April 1, 2016, to March 31, 2018, to create the prediction model for the air conditioning power consumption on the 2nd, 5th, and 6th floors. The explanatory variables are shown in Table 2.

We describe the result for the 5th floor. The trend data were divided into 100 clusters, and the predictive model expression was created for each cluster. Fig. 5 shows the output results of each program.

Table 2. Explanatory variables/Conditional split

Explanatory variables/prospect of conditional split	Note
Decision of working day (working day/holiday)	
Season	
Month	
Day	
Time	
Time elapsed	From 8 a.m. onward
Outdoor temperature	Average value for a time period
Temperature setting	Average value of the air conditioner temperature setting on each floor
Estimated number of people	Number of people estimated from the outlet electricity consumption

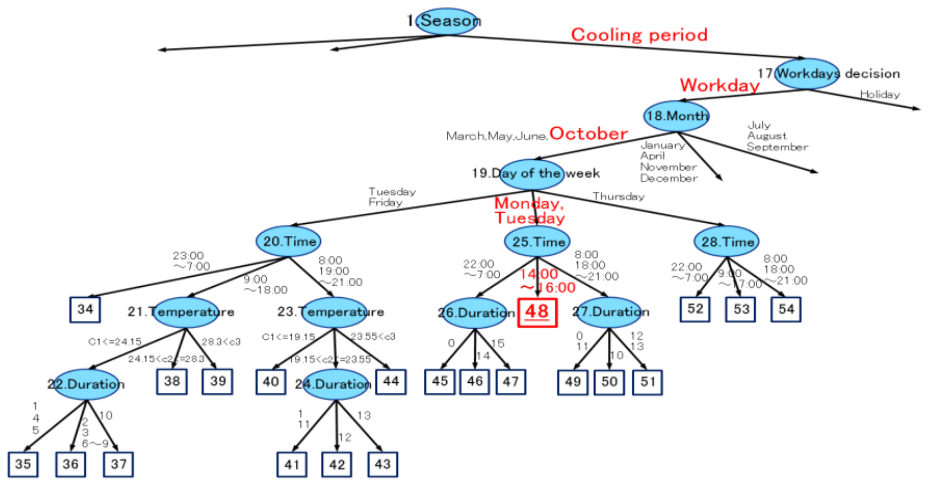
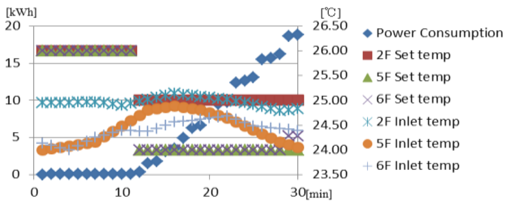


Fig. 5. Split result of trend data.

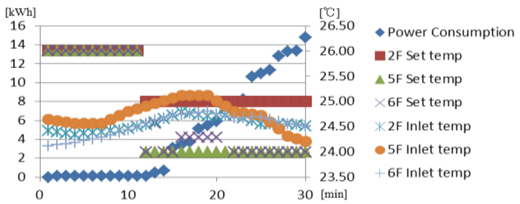
6. Experimental Results

The results of the experiment are shown in Fig. 6. The target value for the first measurement on the first day was 17.8 kWh, and the measured result was 18.8 kWh; the target value for the second measurement on the first day was 15.9 kWh, and the measured result was 14.8 kWh. The result on day 1 was within ±10% of the target value. The target value for the first measurement on the second day was 15.1 kWh, and the measured result was 19.9 kWh; the target value for the second measurement on the second day was 14.9 kWh, and the measured result was 22.7 kWh. The result on day 2 was outside the range of ±10% of the target value.

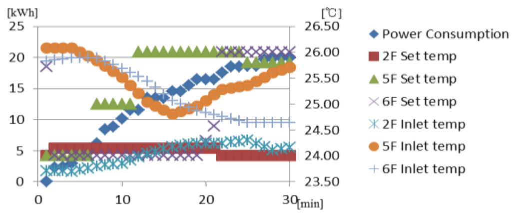
On the 1st day, the temperature setting decreased with time. On the other hand, on the 2nd day, the temperature setting increased with time. Because the outside temperature was high on the 1st day and it was necessary to considerably reduce the amount of electricity consumption, a plan with a high temperature setting was created to result in a large energy saving effect. Because the outside air temperature on the second day was lower than that on the 1st day, a lower reduction in the electric energy was targeted and the control plan with a low temperature setting was created.



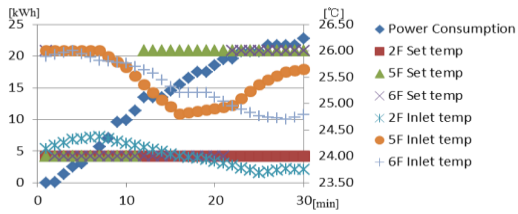
Time of examination	October 1 15:00～15:30
Target value	17.3 kWh
Result	18.8 kWh
Outside temperature	32.6 ℃
Control contents	2F:26 ℃ 10min, 25 ℃ 20min
	5F:26 ℃ 10min, 24 ℃ 20min
	6F:26 ℃ 10min, 24 ℃ 20min



Time of examination	October 1 16:00～16:30
Target value	15.9 kWh
Result	14.8 kWh
Outside temperature	32.6 ℃
Control contents	2F:26 ℃ 10min, 25 ℃ 20min
	5F:26 ℃ 10min, 24 ℃ 20min
	6F:26 ℃ 10min, 24 ℃ 20min



Time of examination	October 2 15:00～15:30
Target value	15.1 kWh
Result	19.9 kWh
Outside temperature	28.0 ℃
Control contents	2F:24 ℃ 30min
	5F:24 ℃ 5min, 25 ℃ 5min, 26 ℃ 20min
	6F:24 ℃ 20min, 26 ℃ 10min



Time of examination	October 2 16:00～16:30
Target value	14.9 kWh
Result	22.7 kWh
Outside temperature	27.2 ℃
Control contents	2F:24 ℃ 30min,
	5F:24 ℃ 10min, 26 ℃ 20min
	6F:24 ℃ 20min, 26 ℃ 10min

Fig. 6. Results of the experiment.

7. Discussion

7.1. Improvement of power prediction model

Twice on the first day, the amount of electric power was extremely low immediately after the start of control, and the control was modified to lower the temperature setting by applying the correction. Because of the change, the amount of power consumption increased and converged to the target value. Unlike on the first day, the power consumption on the second day was high immediately after the start of control, and the control was modified to increase the temperature setting by applying a correction.

In order to analyze the factors that caused such a result, we focused on the conditions before the DR control time period. Table 3 shows the temperature setting before the control and that at the start of control. On the first day, because the control plan was to increase the temperature setting of each floor at the start of control, the air conditioner was set at "Thermo-off" and the conditions at the time when the power consumption was zero were continued. In contrast, because the control plan on the second day was to reduce the temperature setting of each floor at the start of the control, the power consumption amount increased immediately after the start. The control was adjusted by correction, but it did not converge to the target value. Such extreme correction was necessary because we could not predict the change in the power consumption immediately after changing the setting. We believe that we can solve this problem by reducing the time mesh of the data used for learning, for example, from 1 h to 10 min, and by adding the elapsed time from the adjustment of the setting to the explanatory variable.

Table 3. Explanatory variable/prospect of conditional split

	October 1				October 2			
	First		Second		First		Second	
	Before start	Start time	Before start	Start time	Before start	Start time	Before start	Start time
2F	25 ℃	26 ℃	25 ℃	26 ℃	24 ℃	24 ℃	24 ℃	24 ℃
5F	25 ℃	26 ℃	25 ℃	26 ℃	26 ℃	24 ℃	26 ℃	24 ℃
6F	24 ℃	26 ℃	25 ℃	26 ℃	26 ℃	24 ℃	26 ℃	24 ℃

7.2. Fluctuation in temperature setting and variation in room temperature

In this experiment, the change width of the temperature setting with respect to the reference temperature was used as the value for calculating the influence on the consumers. However, it is not the temperature setting but the indoor temperature that actually affects consumers. Table 4 shows the range of fluctuation in the room temperature from the reference temperature at the time of execution of the control plan and the cumulative value of the change width of the temperature setting.

As indicated in bold letters, the difference between the values is as large as 10 or greater. By enabling the prediction of the change width of the room temperature by means of the control system and using it at the time of control planning, it is possible to create a control plan that considers the influence of the temperature fluctuation on the consumers more than the change width of the control meter temperature setting.

Table 4. Change width of the temperature setting

		2F Inlet temp	2F temp setting	5F Inlet temp	5F temp setting	6F Inlet temp	6F temp setting
1-Oct	First	29.09	30.00	13.20	20.00	11.99	20.00
	Second	**16.71**	**30.00**	22.32	20.00	15.68	20.00
2-Oct	First	1.03	0.00	**43.36**	**25.00**	**36.92**	**20.00**
	Second	0.84	0.00	43.12	40.00	**40.47**	**20.00**

7.3. Control plan selection options

In the current program, a control plan that minimizes the total change width of the temperature setting of three floors was selected; the same control plan was executed for a day. When the DR control is executed multiple times, the area in which the energy saving control is frequently executed and the area in which it is executed less often are identified. Because this is a control policy, it cannot be judged as productive or unproductive, but it is beneficial to prepare a mechanism to ensure equitable energy saving control for each area in a building.

Therefore, we propose the following as a method to implement equitable energy saving control for each area in a building.

- After the control is executed, calculate the range of fluctuation of the room temperature in each area and save it.
- In the next control planning, consider the temperature change width in the rooms in each area and prepare a control plan.

8. Conclusions

In this paper, we proposed a method for creating a prediction model and control method for realizing demand response. In the future, we plan to improve the learning model and control program to solve the problem demonstrated in this study.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Toshihiro Mega, Masatada Kawatsu conducted the research; Toshihiro Mega, Yusuke Aoyama analyzed the data; Toshihiro Mega wrote the paper; all authors had approved the final version.

References

[1] Asano H. Lessons learned from experiences in Europe and the US and remaining issues of electricity regulatory reform. *Journal of the Institute of Electrical Engineers of Japan*, 2015; 135(11):766-771.

[2] Yamaguchi S. Impact of the Fukushima Daiichi nuclear power plant accident. *National Diet Library in Japan*, 2011; 718.

[3] Mega T, Kitagami S, Kawawaki S, Kushiro N. *Experimental Evaluation of a Fast Demand Response System for small/medium-Scale Office Buildings*. WAINA 2017, 291-295.

[4] Konno T, Takahashi S, Kitajima H, Teranishi Y, Sonoda T. Evaluation of the demand forecasting methods in a facility type. IPSJ SIG Technical Report, 2013.

[5] Yamamoto T, Uno Y, Nonaka M, Izui Y, Komatsu K, Nikovski D, Xu J. Development of multi-zone building thermal modeling for office building. Presented at: Conference of The Institute of Electrical Engineers of Japan C Society, 2012 .

[6] Kushiro N, Fukuda A, Shimizu T, Mega T. Prediction model for electric power demand in building on field data with extended goal graph and heterogeneous mixture modelling. *Technical report of IEICE Institute of Electronics, Information and Communication Engineers*, 2012; 116(460):39-44.

[7] Fujimaki R, Morinaga S, Eto S, Kanno Y. Research and development of heterogeneous mixed learning technology and big data analysis solution. The 29th Solitary high technology award.