Trend and Technology Development of Demand Response

● Toshihiro Sonoda ● Hironobu Kitajima ● Satoru Takahashi

A Smart City is showing promise as the desired form of a city which can efficiently work with society's infrastructure like energy and transportation ones. In the domain of Japanese energy, an energy management system will change to a distributed system as a liberalized market of power is realized, and it will need a new mechanism where each distributed energy management system can work together with others to keep a good balance between power supply and demand. An ability to meet demand for energy is said to be necessary for the next-generation energy management system. Here we describe the demand response and demand response aggregator that is the key player in the demand response business. And, we explain automated demand response and standardization, the baseline estimate of power demand and the portfolio selection that are needed as functions of a demand response aggregator.

1. Introduction

While resource depletion and global warming rapidly progress due to population increases and industrial development, a Smart City, which can efficiently work with society's infrastructure including energy and transportation ones by making use of information and communications technology (ICT), is attracting attention. In the domain of Japanese energy, electricity liberalization premised on effective use of recyclable energy and separation between power generation and transmission is being actively discussed. When electric power becomes freely marketable, energy will come to be managed by consumers in areas including homes, offices and buildings. In keeping with this, the trend of energy management systems (EMSs) is expected to change from the existing wide-area, overall-management type, which procures the supply of a mega-power station according to the total demand, to a distributed type in which each distributed EMS can work together with others to keep an overall good balance between power supply and demand while energy is managed for each consumer.

As types of distributed EMS, home energy management system (HEMS) intended for homes, building energy management system (BEMS) for offices and buildings and community energy management system (CEMS) for power interchange between communities and procuring power from a power system are under consideration. The result is that demand response (DR), which can maintain the power demand-and-supply balance by coordinating EMSs of consumers, has come under the spotlight.

This paper presents DR and DR aggregator (DRA), which has come into fashion in DR services, and reports on its application study being conducted by Fujitsu Laboratories.

2. DR and DR program

DR is a system in which consumers are requested to reduce power consumption when power supply is tight to adjust the demand, and it thereby maintains a balance between power supply and demand. The power supplier can avoid making an excessive investment in power facilities accommodating the peak power demand by making use of DR to reduce the demand in peak hours and pass part of the saved investment back to consumers.

A specific set of arrangements for realizing DR is called a DR program. DR programs can be roughly divided into two types:

1) Reduction of power consumption in high-rate hours by dynamically changing the electricity rate by the time of day (rate variation-type DR)
2) Reduction of power usage by consumers from ordinary usage by offering incentives in exchange for reducing power consumption at the time of DR events (requests from the power supplier for reduction of power consumption) (incentive-type DR)

The incentive type may be a system of paying for electric energy that can be provided as a DR resource (reducible amount) or paying for the energy actually provided as a DR resource. The former is implemented to have consumers prepare a reducible amount of electric energy to deal with situations in which power supply becomes tight because of a rapid increase in power demand or generator failure, possibly leading to a power outage if things are left as they are. The latter is intended to provide the power supplier with the amount of reduction as a resource, and it is obtained by consumers' complying with the request from the power supplier.

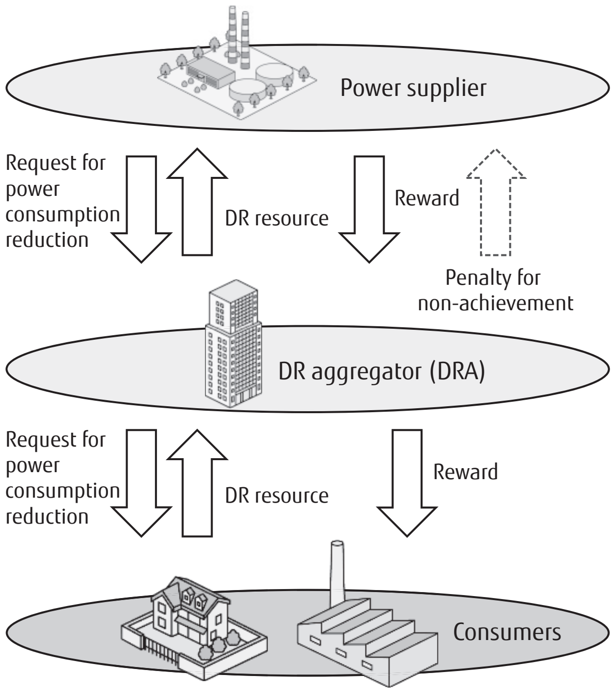


Figure 1
Power supplier, consumers and DRA.

3. DR aggregator

A DRA gathers consumers willing to cooperate in DR for implementing a DR program and also plays the role of guaranteeing a power consumption reduction to the power supplier. **Figure 1** shows the relationship between the power supplier, consumers and DRA. The DRA previously gathers consumers capable of providing a DR resource in order to meet a request for reduced power consumption from the power supplier. When the DRA receives a request for such reduction from the power supplier, it selects consumers that will be requested to reduce their consumption, determines the amount of reduction for the selected consumers, and requests the respective consumers to reduce their consumption. As shown in Figure 1, if the DRA fails to achieve the amount of reduction, it pays a penalty fee to the power supplier. Accordingly, it is important to appropriately select the destinations of DR events and formulate a DR implementation plan (DR portfolio selection) that minimizes the risk of non-achievement of reduction.

In addition, the DRA is required to gather many consumers capable of accommodating DR and be flexible in meeting reduction requests from the power supplier. In order to bring in many consumers and realize a DR program, automation of DR processes (automated DR) and its standardization are essential.

Furthermore, for realizing a DR program, consumers' willingness to continuously cooperate in load reduction is vital. To that end, the DRA must pay consumers reasonable rewards in accordance with their cooperation in reduction of demand and a means to accurately measure the amount of load reduction on which the amount of this reward is based is required. In order to measure the amount of load reduction, it is important to be able to estimate the baseline, which is the amount of power consumption by a consumer while there is no DR event.

The following sections describe Fujitsu Laboratories' approach to automated DR, which is important to a DRA, and its standardization, baseline estimation and DR portfolio selection.

4. Automated DR and standardization

What is regarded as promising as the standard of automated DR is OpenADR, a standard for smart grids. The OpenADR Alliance (non-profit organization that aims to accelerate development and dissemination of

OpenADR)[1] released the OpenADR 2.0a profile specification intended for simple device control in August 2012 and the 2.0b profile specifications supporting a broader range of services was released in July 2013. The OpenADR defines a node that sends a DR event as a Virtual Top Node (VTN: power supplier and DR aggregator) and a node that receives a DR event as a Virtual End Node (VEN: consumer) and specifies information exchange between a VTN and VEN. An example of DR scenario based on OpenADR 2.0b is shown in **Figure 2**. As shown in the figure, the exchange starts with registration of a VEN (EiRegistration service). At the time of this registration, the VEN notifies the VTN of the supported communication system, VEN name, etc. In response to the VEN registration request, the VTN returns the registration identifier, VEN identifier and supported communication system.

Then, the VTN and VEN exchange information about the types of report they are capable of giving (e.g., regular report on power consumption data) in the EiReport service, where a report is requested as required. In this example, the VTN requests the VEN to send a regular report and the VEN sends the report to the VTN as requested. The VTN uses EiEvent service corresponding to a DR event to send the DR event to the VEN. The VEN can decide whether to accept or reject the event in the response. With the OpenADR, a DR event that has once been accepted can be rejected by EiOpt service and vice versa.

Fujitsu Laboratories is working on the development of a prototype of a DR aggregator system based on OpenADR 2.0a and 2.0b.[2]

5. Baseline estimation

It is important to accurately measure the amount of load reduction in order to realize a DR program. And a baseline, which is an estimate of power consumption by a consumer while there is no DR event, is required for measuring the amount of load reduction.

Figure 3 shows the relationship between the baseline, a DR event and actual demand. The ridgeline indicated by the arrow is the baseline, and it shows an estimated demand curve with no DR event assumed. In response to “DR event invocation,” consumers reduce the amount of load promised in the DR program agreement by the “DR event start” time. When notified of “DR event termination,” they return to the normal power usage state. The dashed line indicates the actual power consumption. The difference between the baseline and the actual power consumption between the “DR event start” and “DR event termination” is the amount of load reduction. Depending

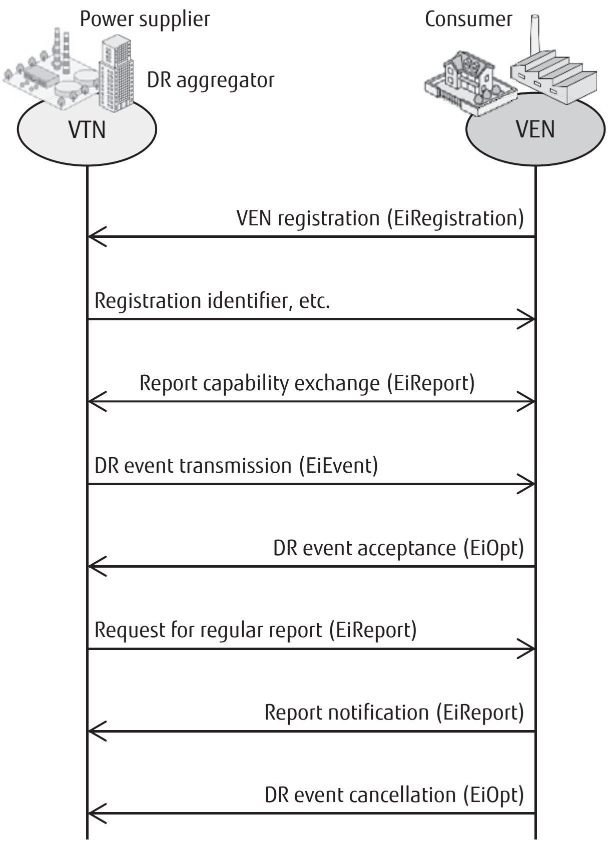


Figure 2
Example of DR scenario based on OpenADR 2.0b.

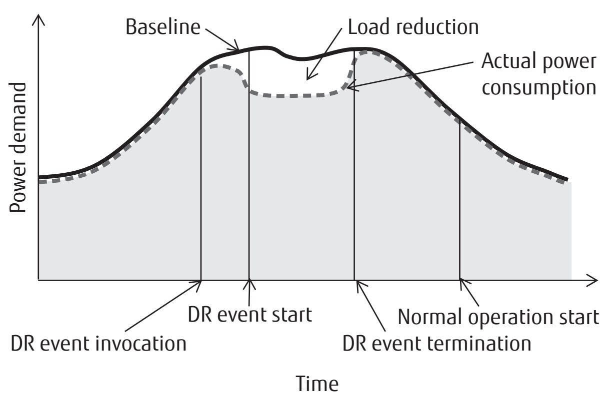


Figure 3
Demand curve and baseline.

on the DR program, a penalty may apply when the promised amount of reduction could not be achieved. Accordingly, it is important to accurately estimate the baseline for both the consumers and the DR program operator. However, the baseline is an estimate after all and it is required to construct a concept of baseline that satisfies all stakeholders including the consumers, DRA and utility company.

Types of baseline are shown in **Table 1**.[3)]

Type I is used in most DR programs and representative methods of this type include the averaging method and the regression analysis method. The averaging method, which is also known as the "High X of Y" method, uses the data for X days with high power usage, out of Y days immediately before the DR event, for calculating the baseline. In the regression analysis method, regression analysis is used for predicting the demand of the day in question based on the past load pattern, weather and day of the week. Reference 3) concludes that, the result of a comparative study of the High X of Y and regression analysis methods shows they are equal in terms of accuracy and the High X of Y method has an advantage in that it is easier to understand.

Type II determines the baseline based on the meter measurement immediately before DR event invocation and is mainly applied to the baseline of an ancillary services-based DR program. In an ancillary services-based DR program, advance notice is not available and the required DR resource must be procured according to the ever-changing conditions of power supply.

Type III does not use past meter data but calculates the baseline based on statistical data. Type IV is a baseline calculation method used when the output of the generator owned by a customer is used as the DR resource actually provided. It assumes the baseline to be 0 for the entire period and measures the output of the generator, which is used as the DR resource.

Table 1
Types of baseline.

Type	Description
I	The baseline is calculated by using past power consumption data.
II	The meter value before/after the start of the DR event is used as the baseline.
III	The baseline is estimated based on similar consumers. Past power consumption data are not used.
IV	The baseline is assumed to be 0 and the output of the consumer's generator is measured as the DR resource.

As a specific approach to energy conservation, Fujitsu Laboratories developed a power demand prediction function for about 70 offices nationwide,[4),5)] and it has been used as a practical service within Fujitsu since 2011. The demand prediction uses a technique combining the "High 3 of 30" method and regression analysis method and we plan to apply it to baseline estimation for DR in the future.

6. DR portfolio selection

A DRA is obliged to pay a penalty fee if the power reduction cannot be achieved, which makes it important to formulate a DR implementation plan that mitigates the risk of penalty payment as much as possible. This can be addressed by the system developed by Fujitsu Laboratories to minimize the risk of non-achievement of reduction (DR portfolio selection), which is described below. Here a DR program with a DRA directly controlling air conditioning [air conditioning direct load control (DLC)] is taken as an example to explain portfolio selection. The following procedure can be assumed for a DR implementation plan in air conditioning DLC.

1) Determination of the period of implementation of air conditioning DLC and reduction target
2) Prediction of reduction of each site based on the outdoor temperature (forecast value) and the temperature setting increment (in summer) during DLC implementation
3) Selection of a combination of sites under DLC that satisfies the reduction and determination of the increment

The most difficult step in this procedure is 3). Aside from modeling errors of the demand model, etc., non-negligible divergence may stochastically occur between the expected and actual amounts of reduction for reasons including errors between the forecast and actual values of outdoor temperature. When there are many combinations of sites that satisfy the reduction target, it is not easy to select one of them to lead to a reliable result.

This situation is similar to a case where investors select from a combination of assets targeted for investment. In the domain of financial engineering, etc., the optimization method that helps investors select from a combination when the expected value and variance of the rate of return for the respective investments are known is widely known as a mean-variance model[6),7)] for a "portfolio selection problem." The following describes how this type of method can be applied to a DR resource combination.

As an example, it is assumed there are multiple areas that have access to temperature forecast values and there are multiple sites (such as homes and offices) in each area under the supervision of a DRA and the administrator formulates an air conditioning DLC plan. Air conditioning DLC planning ultimately involves determining the period of DLC, target sites and specific temperature setting increment (in summer). Here we discuss a plan for the respective area directly affected by temperature forecast errors.

First, the demand reduction r_i of area i and temperature forecast error δT_i are modeled by using the expressions below. δT_i is handled as a stochastic variable that is normally distributed.

$$r_i = A_i \Delta t_i + B_i \delta T_i$$
$$\delta T_i \sim N\,(0, \sigma_i^2) \qquad 1)$$

Where Δt_i is an increment of the air conditioning temperature setting and A_i and B_i are constants determined by estimating linear models of air conditioning demand for the respective sites and aggregating them for each area. The demand reduction of area i also has a normal distribution as shown below.

$$r_i \sim N\,(\bar{r}_i, \sigma_{Bi}^2)$$
$$\bar{r}_i = A_i \Delta t_i$$
$$\sigma_{Bi}^2 = B_i^2 \sigma_i^2 \qquad 2)$$

Here we consider the DLC planning problem for each area as a problem of finding the allocation of the amount of reduction that provides the smallest distribution of the amount of reduction with the given overall reduction target R^{AC} (<0) as the expectation value. As a practical limitation, the temperature setting increment has an upper limit, which is represented by Δt^{max}, and the ratio of the actual increment for area i corresponding to the temperature setting increment is represented by y_i. Using these for formulating the optimization problem leads to a quadratic programming problem:

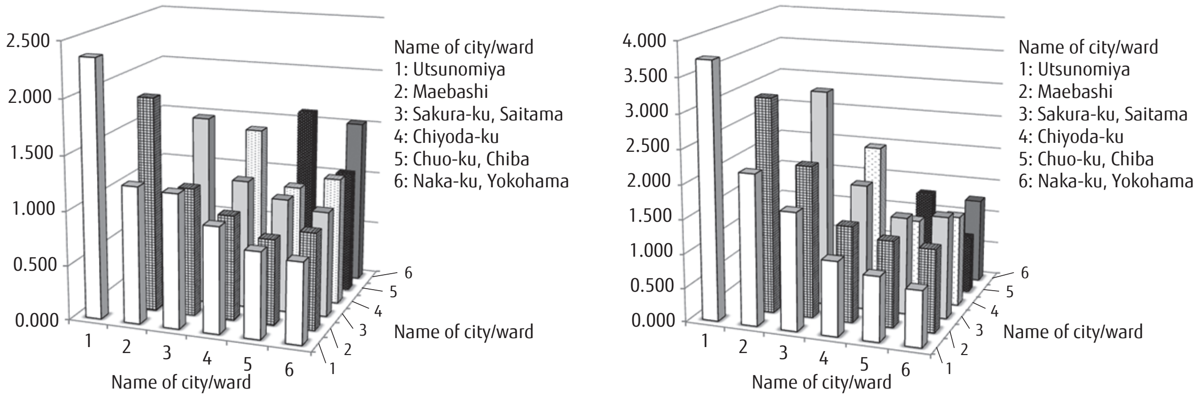
$$\min: y^T Q y$$
$$\text{s.t.}$$
$$R^{AC} = y^T \bar{r}^{max},$$
$$0 \le y_i \le 1,$$
$$\text{where}$$
$$y_i = \Delta t_i / \Delta t^{max}\ ,\ \bar{r}_i^{max} = A_i \Delta t^{max}$$
$$Q = \begin{pmatrix} B_1 B_1 \sigma_{11} & \cdots & B_1 B_n \sigma_{1n} \\ \vdots & \ddots & \vdots \\ B_n B_1 \sigma_{n1} & \cdots & B_n B_n \sigma_{nn} \end{pmatrix} \qquad 3)$$

Matrix Q above is a variance-covariance matrix, hence positive semidefinite, and this problem has a global optimal solution.

For the purpose of estimating the effect of portfolio selection in air conditioning DLC, we conducted a numerical experiment. For this experiment, six urban areas in the Kanto region (the region including Tokyo and six surrounding prefectures) of Japan were assumed and the actual forecast and measured values of outdoor temperature for the respective areas were used. A commercial value forecast service was used to obtain the forecast values.

Figure 4 shows the covariance of the errors of outdoor temperature forecast in five cities and one ward in Kanto in July 2012 used for the experiment calculated separately for the first- and second-half periods. For portfolio selection in DLC to be effective, the covariance relationship between forecast errors at the time of the determining the selection is similar to that at the time of implementation. This example shows that, while values are generally larger in the second half of July, the relative relationship between areas is maintained to a certain extent.

Next, the reduction allocation ratio optimized by using the forecast error information for the first half of July was applied to the second half of the month to calculate the rate of improvement in the deviation of reduction. As a result, a comparison with reference to the worst selection (the entire amount of reduction allocated to the area with the largest forecast error) and equalized selection (the amount of reduction equally divided between the areas) has shown that improvement effects of around 38.9% and 6.35% respectively



(a) Covariance of outdoor temperature forecast errors (July 1 to 15, 2012)

(b) Covariance of outdoor temperature forecast errors (July 16 to 31, 2012)

Figure 4
Covariance of forecast errors for five cities and one ward for two periods.

were achieved as compared with the respective deviations.

7. Conclusion

Demand response (DR) is attracting attention as a system for coordinated operation of consumers' EMSs. This paper has presented DR and a demand response aggregator (DRA), which is the key player in DR services. It has also reported on automated DR, which is essential to the development of the DRA business, and DR standardization, baseline estimation and portfolio selection. Portfolio selection has been confirmed to be capable of mitigating the effect of temperature forecast errors, which may cause uncertainty in DR implementation.

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Toshihiro Sonoda
Fujitsu Laboratories Ltd.
Mr. Sonoda is currently engaged in research related to energy solutions.

Satoru Takahashi
Fujitsu Laboratories Ltd.
Mr. Takahashi is currently engaged in research related to energy solutions.

Hironobu Kitajima
Fujitsu Laboratories Ltd.
Mr. Kitajima is currently engaged in research related to energy solutions.