Energy Management System, *s*EMSA, to Realize Carbon Neutral Society

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In an effort to create a decarbonized society, Japan, Europe, and the United States are shifting their main energy sources from fossil fuels to renewable energy sources such as solar power. However, the output of renewable energy sources fluctuates depending on weather conditions, making it difficult to provide a stable supply of electricity. As a solution to this problem, efforts are being made to introduce distributed power sources such as small- and medium-scale solar power generators and storage batteries on the consumer side to level out the output fluctuations of renewable energy. As renewable energies are introduced in large quantities in the future, energy management systems will play an important role in integrating distributed power sources and operating them stably and efficiently. This paper discusses a next-generation energy management system that organically links distributed power sources and controls them in an integrated manner. We first discuss the technical challenges of integrated management of distributed power sources, and then summarize the prior technological trends toward the solution of these challenges. Finally, the features and application areas of our energy management system "*s*EMSA-μGrid" are explained.

Keywords: renewable energy, autonomous power systems, demand prediction/power generation prediction, VPP, microgrid

1. Introduction

With the aim of creating a decarbonized society using renewable energy as the major energy source, renewable energy power plants, such as solar power and wind power plants, are being newly constructed, and renewable energy facilities are being actively introduced to energy consumers. The power system is shifting from a centralized system based on large-scale power sources to a decentralized system based on distributed power sources, such as solar power and storage batteries, dispersedly located at consumer sites. The number of power plants in Japan has increased from several hundred in the early 2000s to more than 4,000 in 2021. With further progress in the introduction of small- and medium-scale distributed power sources as a result of the implementation of institutional reforms and other measures, stably controlling millions of distributed power sources will become necessary in the future.

Controlling centrally such a large number of distributed power sources in a conventional manner is difficult in terms of the volume of communication and information. To overcome this difficulty, research on next-generation power systems is being actively conducted mainly in Europe and the U.S. For example, an Advanced Research Project Agency-Energy (ARPA-E) project, which was launched by the National Renewable Energy Laboratory in the U.S., is conducting research and development on autonomous dispersed and hierarchical power systems. According to this research, if the concept of the project is realized, 4.9 GW of power supply reserve, which is worth $3,300 million annually, will be created in the U.S. Toward the realization of the concept, the above project has proposed a model consisting of three stages: prediction, optimization planning, and control.[(1),(2)]

At Sumitomo Electric Industries, Ltd., we have been conducting research and development on next-generation power systems. In terms of research results, we issued a press release on *s*EMSA-μGrid in June 2021.[(3)] In addition, the ultimate goal of this R&D project is to realize an Eco-friendly society, and contributes to a series of activities related to SDGs by the Sumitomo Electric group. In this report, we summarize the problems associated with next-generation power systems, explain such element technologies of *s*EMSA-μGrid as prediction, optimization, and control, and then discuss future research challenges.

Fig. 1. Contribution to SDGs by the Sumitomo Electric group

2. Problems Associated with Next-Generation Power System

As a next-generation power system, research on hierarchical architecture is being actively conducted. In Japan, a hierarchical architecture has been proposed as a means of realizing a Virtual Power Plant (VPP). This architecture consists of a resource aggregator that bundles distributed resources installed at energy consumer sites and an aggregation coordinator that further bundles resource aggregators at the upper level.(4)

In this architecture, each layer plays an assigned role. For example, the consumer layer is expected to control the distributed power sources installed at the consumer sites so that the output of these sources will be consistent with with the receiving-point-based control target values. The upper layer is expected to bundle multiple consumers and exert control such that the sum of the power at the receiving points is consistent with a planned value. This concept is called hierarchically planned power receiving and is shown in Fig. 2. The following practical example shows that it is very difficult to exert control such that the power at a power receiving point is precisely the same as a target value.

Figure 3 shows the results of an investigation into the short-term fluctuations (one-minute differences) of the power received by a domestic extra-high-voltage customer for three months. The contracted power of this customer was about 10,000 kW. When the demand data were collected in one-minute intervals and the differences were calculated, the average demand was 51.4 kW (0.514%), but short-term fluctuations exceeding 200 kW (2%) can be seen like Gaussian noise.

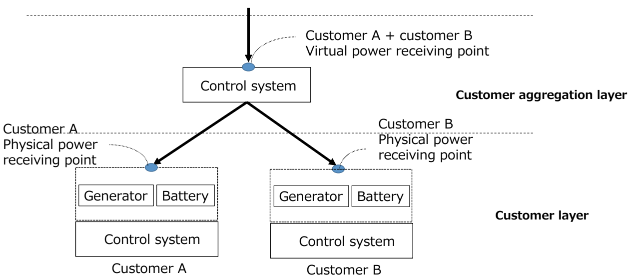

Fig. 2. Concept of hierarchical power control systems

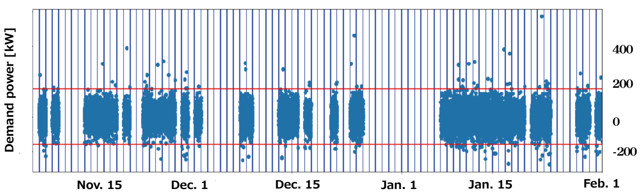

Fig. 3. Short-term fluctuations of receiving point

The above consumer is required to maintain the received power within ±120 kW of the control target value. In other words, although demand and power generation prediction technology for a 30-minute average is generally important, it is also necessary for control on the order of minutes or seconds not to rely on only prediction technology but to use a combination of fine cycle control that can respond to short-term fluctuations while utilizing prediction technology.

Next, we discuss the control of virtual power receiving points that bundle consumers. The control system at each node of the hierarchical architecture is required to operate cooperatively. The problem is that the control system made by each manufacturer has its own control trend and mounting characteristics and they may cause control errors in bundling the consumers. We have accumulated experience in connecting our control systems with those made by other companies through the VPP demonstration and other projects launched by the Ministry of Economy, Trade and Industry, and we are analyzing the technical problems we will be confronted with when realizing a large system consisting of subsystems made by multiple companies. One of the problems revealed by our analysis is the relationship between the control commands sent from our system to other companies' systems and their responses to the commands (control performance). In fact, we have found that the control performance tends to exceed or fall below the expected value. For example, Fig. 4 shows the normal distribution obtained by the Smirnov-Grubbs test*1 on the difference between the control command values issued by a control system that bundles two consumers and the actual measured values. In this figure, zero means that the command value is equal to the actual value, a positive value means that the actual value is smaller than the command value, and a negative value means that the actual value is larger than the command value. Although there are two cases of error in which the actual value is larger or smaller than the command value in this example, the actual value is averagely larger than the command value. Errors are caused by various factors and have various characteristics. We believe that an error and its characteristics are affected by characteristics of manufacturers' implementation.

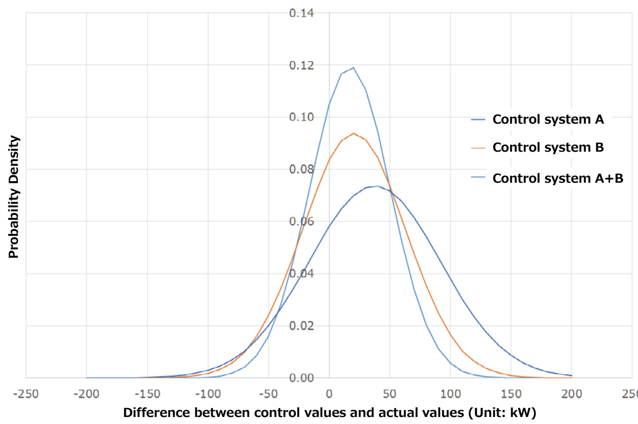

Fig. 4. Probability density function of control error (after statistical hypothesis testing)

Another problem is the response time of the resource. Let's assume that a generator is the control target. A certain amount of time is required for the generator to reach a desired output after receiving a control command. Depending on the types of resources managed by the control system, the response time after a control command is issued needs to be considered.

In addition, there are certain cases where the control command values issued between control systems exceed the output of the generator and the charge/discharge capacity of the storage battery, which are the control targets in the consumer layer. This is because the temporal granularity of the control target is coarser in the upper layer of the control system, increasing the difference in control command value between before and after the granularity boundary. Depending on the response time of the generator and the state of charge of the storage battery in the consumer layer, the generator may not be able to follow this large change in command. In other words, when issuing a control command from one control system to another, control errors may occur unless the characteristics and status of the control resources of the latter control system are understood and adapted as needed.

As described above, cooperative behavior between multiple control systems is important to realize a hierarchical control system, and for this purpose, it is important to adapt the control flexibly in response to the unique control trends of the control system and the characteristics of the resources, such as generators and storage batteries, to be controlled. The prediction, optimization, and feedback control technologies, which are key to achieving this purpose, are discussed in the following chapter.

3. Related Technologies and *s*EMSA Technology

3-1 Demand prediction technology

There are various types of demand prediction, such as predicting area demand over a wide area covering thousands or tens of thousands of consumers, which has been traditionally conducted by electric power companies, and predicting the demand per consumer for imbalance avoidance and self-consignment. A typical demand prediction model predicts future demand by capturing the characteristics of the following demand data.

- Periodicity: The idea of periodicity is based on the following example assumptions: The demand on Monday is nearly equal to that on Mondays of the previous week and the week before last. The demand from 9:00 to 9:30 a.m. on a given day is nearly equal to that during the same time period on the previous day.
- Continuity: Continuity is based on the assumption, for example, that the demand from 9:00 to 9:30 a.m. is nearly equal to that from 9:30 to 10:00 a.m.
- Correlation: Correlation is based on the assumption, for example, that demand is correlated with weather and demand during a hot summer day is nearly equal to that during another hot summer day.

Figure 5 shows an image of the method for analyzing demand data with a focus on periodicity. The daily data were divided into 24 hourly data sets, and the data for the same time zone over several months were aggregated and their probability density function was analyzed. It can be seen from this figure that the patterns of the average, variance, and number of peaks differ depending on the time zone.

A moving-average model, autoregressive model, and autoregressive moving average model as well as the application of a support vector machine and neural network that use machine learning and artificial intelligence, have been proposed as demand prediction models. For example, the hourly averaging method is also used as a baseline for demand response. The calculation method is very simple. It uses the average of the measurements during the last N days of each time period as the predicted value. The autoregressive model uses its own values in the past to explain future behavior. A multivariate autoregressive model expresses the prediction target using the time series of itself and several other variables, such as outside air temperature, humidity, wind velocity, intensity of solar radiation, and other pieces of weather information.

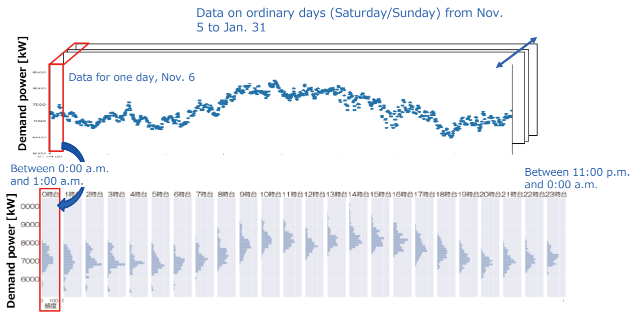

Fig. 5. Analysis of demand data for demand prediction

At Sumitomo Electric, we have been promoting research and development on several demand prediction models in order to create a mechanism that will enable us to select the model appropriate for a specific consumer and flexibly change the model to be applied. There are many cases where models do not fully meet the needs of extra-high-voltage consumers unless the models are customized. We also provide a service that analyzes consumers' power data and customizes certain prediction models so that they meet such customers' specific needs.

Demand data often changes rapidly depending on the site, as shown in Fig. 3. One of the countermeasures is to absorb such demand changes by using storage batteries having a quick charge/discharge switching cycle. However, if the demand changes exceed the capacity of the storage battery installed, the charge/discharge of the storage battery will not be able to absorb the changes in demand. Therefore, it is important in system design to estimate the optimal requirements for the storage battery to be installed at each site while using a short-term demand change as one of the focus points. In other words, the charge/discharge capacity required of the storage battery is estimated from the allowable variation of demand and the short-term variation of demand in the past. We are developing a technology that will be able to estimate by simulating the optimal capacity of the storage battery. This technology analyzes past demand data, separates the demand into components that can be predicted by a demand prediction model and those that cannot be predicted (noise components), and analyzes the probability density function of the noise components.

3-2 Solar power generation prediction technology

Several prediction models are used for solar power generation, including a numerical prediction model that uses weather forecast information for modeling, a statistical model that performs the prediction based on the continuity of the time series of the latest measured data, and models that use machine learning and artificial intelligence techniques.[(5),(6)]

The numerical prediction model uses a certain model to predict future weather conditions. In particular, the numerical prediction model divides the atmosphere, oceans, and land into small grids, estimates the data value of the atmospheric temperature, wind, and land surface temperature of each grid, and predicts the rise and fall of temperature due to wind movement and sunlight. Numerical prediction models are mainly used to predict several weeks to several hours ahead.

The statistical model uses the data obtained by measuring solar power generation. This model grasps weather data as time series data and predicts future weather data values up to several hours ahead based on past measured data. The models used include autoregressive models and autoregressive moving average models, and the basic idea of the statistical model is the same as that of demand prediction. Another variant of this model is the exponential smoothing model, which predicts the future by weighting past data (larger weighing value for more recent data). This statistical model is usually used to predict several hours ahead.

Another approach is to use machine learning and artificial intelligence techniques. The latest trend is the use of neural networks and support vector machines. This method uses measured data, such as solar power and weather data, as training data and fits these data to the model to predict future power generation data. Statistical models are used for short-term prediction, while machine learning is used for a relatively wide range of prediction, from short-term to next-day prediction.

*s*EMSA makes medium-term predictions from several hours ahead to the next day in order to enable the organization for cross-region coordination of transmission operators in Japan to draw up a plan for the next day. This energy management system also makes short-term predictions of one hour ahead for the purpose of drawing up a plan for the day before the gate closes. For medium-term predictions, a numerical prediction model is used as a base model, and the tilt angle of the solar panels and various other pieces of information are added. By collecting power generation data from power generation sites on a real time basis, the power generation prediction of the numerical prediction model is corrected (feedback correction) to make more recent power generation predictions. In addition to these models, we are conducting research and development on statistical models and machine learning models that use weather clustering and support vector machines.

These models are general prediction techniques and remain at the academic level. For practical use of them, it is important to take them one step further until they can make predictions more accurately by extracting the characteristics specific to each power generation site. For example, the shadows cast by buildings over the solar panels at certain times of the day reduce the power generation only during those times, and the correlation between solar radiation and power generation will change if the solar power system fails. In practice, it is necessary to make predictions after taking into account these specific characteristics of each solar power generation system.

3-3 Control technology

*s*EMSA consists of two major control functions. One is the function to control demand so that it will never exceed a certain amount on a power receiving point basis (peak shaving, prevention of reverse flow of solar power, and so on), while the other is the function to control demand so that it will be always consistent with a certain amount on a power receiving point basis. The former is realized as rule-based control, while the latter is realized as feedback control.

Rule-based control can be used for demand control to prevent demand power from exceeding a certain amount and for output control of solar power generation to prevent the output from exceeding demand and thus to prevent reverse power flow. Demand control reduces a certain load when demand power exceeds a preset threshold, thereby preventing demand from exceeding contract demand. For example, whether or not demand will exceed the contract amount is judged at 20 and 50 minutes past the hour, and if it will, the load is reduced. The output control function for solar power generation, for example, controls the output of a solar power generation plant installed at a certain location to prevent an excess amount of power from flowing backward into the grid when the output exceeds demand at that location. The solar power generation amount and demand are monitored constantly, and when reverse power flow is expected to occur at a high probability, the control system stops the solar power generation system or reduces its output. Since the output of solar power generation fluctuates rapidly, it is necessary to monitor and control the output on a second-by-second basis.

Rule-based control defines conditions and actions. An example of the conditions is “demand power exceeds a certain amount,” and that of the actions is “reducing a certain load.” The challenges of the control are conditional decision-making cycle and the control delay from conditional decision making to actual control. If the conditional decision-making cycle and control delay are large, the conditional judgment needs to be made with a sufficient allowance. If not, the solar power generation system may be stopped to suppress its output although such an action is intrinsically unnecessary, resulting in degradation of solar power generation efficiency.

Feedback control is used to control power receiving points so that the power received at these points is in conformity with a certain value. This type of control can be used for simultaneous balancing of planned demand-supply and tertiary supply-demand adjustment markets. Proportional-integral-derivative (PID) control-based logic is usually used.[(7)] Proportional (P) control reflects the difference between the most recent command value and the measured value. Integral (I) control takes into account the accumulation of past control commands. Derivative (D) control predicts the future from the most recent trend. One of the challenges in applying PID control to a power system is the weighting of the P-, I-, and D-controls, which is highly dependent on the characteristics of the other control systems linked to the power system and those of the resources to be controlled.

The rule-based control of *s*EMSA makes conditional judgment in the shortest cycle of one second to minimize the control delay. If the condition is true, *s*EMSA issues a control command with a delay of less than a second. Since the threshold for conditional judgment is set by parameters, it is possible to set the values after optimizing them for the demand pattern, power generation pattern, and other characteristics of each site. (The monitoring cycle and the fluctuation range of demand and power generation within the cycle are considered.)

The feedback control of *s*EMSA is based on the concept of PID control. As for the weighting of P-, I-, and D-controls, which is one of the challenges in applying PID control to power systems, the feedback control performs initial tuning by simulating the local environment prior to the introduction of the system and maintains appropriate values by periodically monitoring and updating them as needed after operation of the system. Regarding the range of past time to be considered in I-control, *s*EMSA is provided with a mechanism that makes it possible to appropriately tune the range depending on the application. For example, in the application of the feedback control to simultaneous balancing of demand-supply, the demand time limit is switched at 30-minute intervals. On the other hand, when using *s*EMSA in a supply-demand adjustment market, it is necessary to set the cycle to one or a few minutes. To meet such market needs, *s*EMSA is equipped with a mechanism that can switch the range of past time according to each use.

3-4 Optimization technology

*s*EMSA is equipped with an optimization control function that shifts demand peaks by controlling the generators and storage batteries and draws up a control operation plan to minimize total operating costs, including purchased electricity and fuel costs. The above function optimizes the timing of starting and stopping generators and the timing of charging and discharging storage batteries for tens of hours in the future based on the prediction of demand and power generation on the basis of certain indicators. In order to achieve this function, *s*EMSA employs mathematical programming. In mixed linear programming, the objective function (e.g., cost minimization) and its constraint conditions (e.g., maximum output of the generator) are expressed in the form of linear equations, and the solution is obtained as a combined optimization problem. As an application example, Midcontinent Independent System Operator (MISO), an independent power transmission and distribution system operator in the U.S., has applied mixed linear programming to a supply and demand system to draw up an optimal power generation plan that satisfies demand with the capacity of the power grid as a constraint condition.[8] We have also been conducting research and development on optimization planning since 2013 with the aim of applying it on a full-scale basis to large-scale plants and VPPs, and we have already produced some good results.[9],[10]

One of the features of *s*EMSA is that it has been equipped with an architecture that combines multiple optimization solvers[11],[12] to obtain an optimal or pseudo-optimal solution in a minimal time period. Many of the mathematical optimization problems to be solved by *s*EMSA are NP-hard problems.*2 Simple modeling and application of solvers are not enough to solve the above problems. In the formulation of generators and storage batteries, we solve these problems by abstracting the generators and storage batteries in such a way that the solutions can be obtained on a real time basis while maintaining the operating specifications of the actual equipment and by modeling the problems after considering the characteristics of the solvers.

As a concrete example of the model equation, the output range, efficiency, ramp-up time for starting and stopping, and output change time can be set by parameters, and these set values are tuned as equipment-specific values. In addition, the hierarchical architecture requires interconnection between control systems of multiple vendors as described in Chapter 2. To meet this requirement, it is necessary to consider the characteristics of each control system, such as its unique control trend and the response time specific to the controlled resource. *s*EMSA has modeled various factors, including the characteristics of other companies' control systems, and achieves highly accurate control.

4. *s*EMSA-μGrid

The core technologies described in the preceding chapter have been elaboratively integrated to realize hierarchically planned power receiving. Figure 6 shows an example of the control results of a demonstration of the tertiary supply-demand adjustment market in the VPP demonstration project launched by the Ministry of Economy, Trade and Industry, in which two sites are aggregated. The planned values are almost equal to the actual values for four hours, which is the DR period, verifying that the hierarchically planned power receiving described in Chapter 2 has been realized.

We packaged the functions described above as a core technology and issued a press release on it as *s*EMSA-

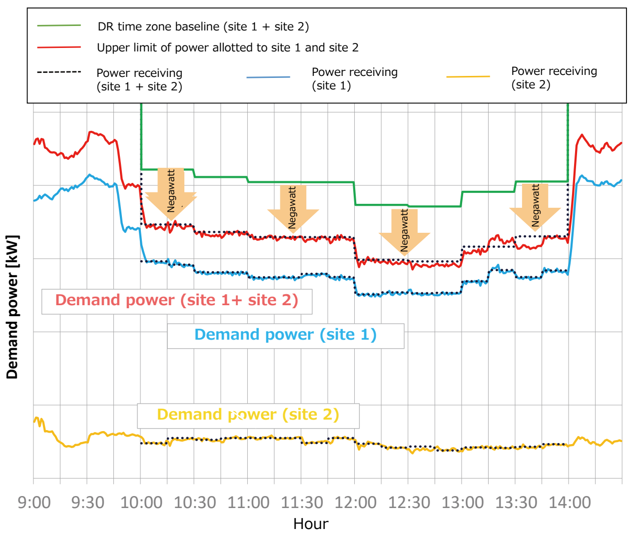

Fig. 6. Actual results of hierarchical power control by *s*EMSA

μGrid on June 24th, 2021. Figure 7 shows an example of the system configuration of *s*EMSA-μGrid. The package consists of a VPP package, a decarbonization package, and a microgrid package. The VPP package meets the needs of power source I’*3 and supply-demand adjustment markets, and it has already been supplied to several electricity retailers. The decarbonization package, which meets the needs of plants and retail facilities intending to decarbonize, has an optimal planning function that maximizes private consumption of renewable energy and peak shaving. The microgrid package is for use in a municipality or at a new regional electric power company and has various functions, such as integrated surveillance and control of government office buildings, community centers, and other municipally owned facilities. This package also has the ability to transmit on consignment surplus power generated by a solar power generation system installed at one site to another site.

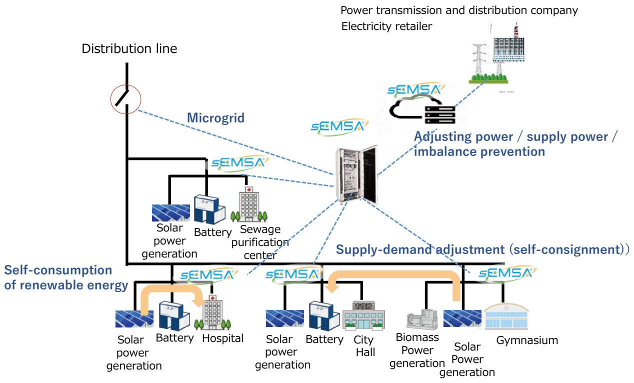

Fig. 7. An example of the system configuration of *s*EMSA-μGrid(3)

*s*EMSA has been designed with a hierarchical model, which is a next-generation power system architecture, in mind. The hierarchical model consists of multiple layers of independent distributed nodes. The lowest layer node directly controls distributed power sources, while the higher layer nodes integrate multiple lower layer nodes. Measurement information, adjustable information, and control command information are exchanged between the layered nodes. Since this interface is basically the same for all layers, scalability can be realized by increasing the number of layers.

5. Conclusions

In this paper, the authors discussed the architecture required of next-generation power systems, the trends of the latest technology for realizing the architecture, and the main technical points of *s*EMSA. Decarbonization and the realization of a sustainable society is a global trend. In line with this trend, research and development on the new concepts of power systems are being actively conducted both in Japan and overseas. We will contribute to society through *s*EMSA.

Technical Terms

*1 Smirnov-Grubbs test: A method of testing whether or not extremely large or small values are abnormal values when the population of data follows a normal distribution.

*2 NP-hard problem: A problem that makes it extremely difficult to obtain its solution since the calculation time increases explosively as the scale of the problem expands.

*3 Power source I’: One of the menus of adjustment power, which responds to demand surges during severe weather, such as extreme hot and severe cold temperatures.

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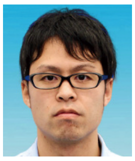

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