Long-term Load Forecasting of 9-Japanese Power Utilities Considering the Enhancement of Energy Conservation

日本では電力ユーザーが自由に供給者を選択できる電力自由化時代が予想されている—様々なシナリオを考慮して長期電力需要を予測する。

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Abstract The trend of electricity demand in Japan has increasing rapidly and the load factor of total power system decreased in the past twenty years. However, due to the new energy conservation policy, one report says that the demand for electricity in January 2012 decreased by 3.7% compared with the previous year, of the total electricity sold by the 10 electric power companies in Japan. In the industrialized countries, the increase is, however, only about 1 to 2 percent per year with an estimated doubling of the demand in 30 to 50 years. In the next 20 years, power consumption in developing and emerging countries is expected to more than double, whereas in industrialized countries, it will increase only about 40 %. Due to the recent power deregulation in Japan, construction of big power plants will be stopped and some IPP and PPS, which are mostly thermal power plant and renewable energies, will be set up near the demand in order to control supply-demand for the loads. In this research, various scenarios of future restructured power systems are discussed from the point of view of maximum electric power demand prediction in the long term.

Keywords Load forecasting; Maximum electric power demand; Energy conservation

1. Introduction

Electric power companies in Japan are regulated by the Electric Utility Industry Law. The law was amended in 1995 to open Japan's generation and wholesale supply markets to independent power producers. The main change was to permit independent power producers to supply power to the traditional electric utilities. This was the first stage of electric industry deregulation in Japan.

In 1999, the law was amended again to facilitate greater deregulation. The amended law, which went into effect in March 2000, partially liberalized the retail segment, permitting large-scale consumers to choose their own electricity supplier. Here, "large-scale consumers" refers to those consumers who have a peak demand of more than 2 MW and a voltage level of 20 kV or higher. Power sales to such consumers account for about 30% of Japan's total power sales.

The 1999 amendment further promoted competition by permitting utility companies to supply power to large-scale consumers outside of their primary service region. To allow Independent Power Producers (IPPs) and power marketers to use the transmission and distribution lines owned by the traditional utilities a fair and impartial process was mandated.

Utilities were to determine transmission rates, as well as the terms and conditions in accordance with Ministry of Economy, Trade and Industry (METI) guidelines. [1)]

In this paper, we will be discussing the application of long-term load forecasting, considering restructuring power systems in Japan. The necessity of introducing renewable energies with distributed generation and case studies with certain scenarios are considered for the new environment to predict the maximum electric power demand in future years.

2. Selection of Suitable Economy Factors for Maximum Electric Power Demand Prediction

A careful investigation of the selection of related parameters as economic factors for long-term load forecasting shows the following factors influence the electric power demand. These factors are later used as inputs in the networks.

A. *Selected Economy Factors*

1. *Gross National Product (GNP).* GNP serves as a measure of the size of the nation's economy. It has also long been used as an indicator of economic trends.
2. *Gross Domestic Product (GDP).* GDP shows the size of economic activity and economic conditions that occur within a country. In view of the increase in Japanese investments overseas, Japan, too, changed the base of statistics from GNP to GDP in 1993.
3. *Population.* It is thought that the demand for electric power will increase in proportion to the population.
4. *Number of households.* Households are taken into account as an important factor, because of the existence of many appliances in each household.
5. *Summer days.* The temperature causes an effect of electric power demand. In the summer days people usually use air conditioners, a big portion of power consumption. And thus the number of summer days is taken as a factor of the network.
6. *Cool days.* Nowadays multiple air conditioners are used in different rooms of a household. In addition, the duration of its usage is longer than that of washing machines, vacuum cleaners, etc. For the cool days, it causes a heavy power consumption to keep the rooms warmer using electricity. That is why the number of cool days is also taken as an factor of the network.
7. *Index of Industrial Production (IIP).* The entire industry movement can be achieved by using IIP as a factor.
8. *Oil price.* Crude oil price exert an influence on the generating electricity cost. If crude oil prices fall, electricity generation cost fall, and electric charges finally fall.
9. *Electricity price.* It is thought that when the price of electricity decreases, the amount of unnecessary electric power consumption increases gradually.
10. *Maximum Electric Power.* The maximum electric power of the previous year is also used as one of the factors of the network.

B. *Contribution Factor*

In this paper, an additional important approach called "Contribution Factor" is presented to determine the level of influences of selected inputs on output. The contribution factor is the sum of the absolute values of the weights leading from the particular variables. The entire data set is checked before training the RBFNs. This function produces a number for each input variable called "a contribution factor" that is a rough measure of the importance of that variable in predicting the network's output relative to the other input variables in the same network. The higher the number, the more the variable is contributing to the prediction. We can use the contribution factor to decide which variable to remove in order to simplify the network and make the training faster. However,

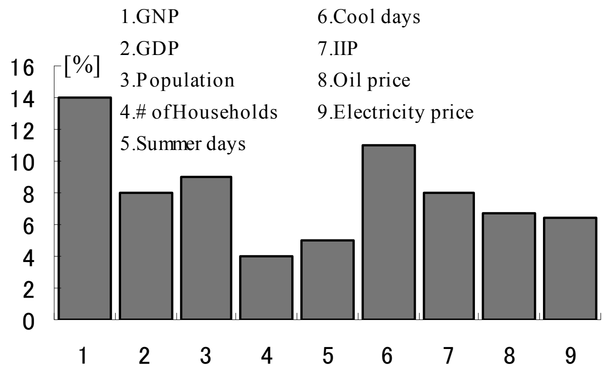

Fig.1 Contribution Factors of Selected Inputs

we should probably only do this when the number of inputs exceeds approximately 100.

It should be noted that the value of a contribution factor should not be considered “gospel” when deciding whether to include a variable in a network. Neural networks are capable of finding patterns among variables when none of the variables themselves are highly correlated to the outputs. Obviously, if a certain variable is highly correlated with the output, the variable will have a high contribution factor.

The number of input variables also affects the contribution factor. For example, if we include more than 60 to 80 input variables, sometimes the contribution factors get very close to each other and we cannot differentiate among the variables. The contribution factor of remaining inputs is shown in Fig. 1. The Y-axis of this Fig. 1 shows the percentage of the influence of each input on the output.

3. Network Model for Prediction

A Radial Basis Function Network (RBFN) in most general terms is any network, which has an internal representation of hidden processing elements (pattern units) which are radically symmetric. For a pattern unit to be radically symmetric, it must have the following three constituents:

- A center, which is a vector in the input space and which is typically stored in the weight vector from the input layer to the pattern unit.
- A distance measure, to determine how far an input vector is from the center. Typically, this is the standard Euclidean distance measure.
- A transfer function, which is a function of a single variable, and which determines the output of the PE (processing elements) by mapping the output of the distance function. A common function is a Gaussian function, which outputs stronger values when the distance is small.

In other words, the output of a pattern unit is a function of only the distance between an input vector and the stored center.

The network architecture, characteristics and the learning strategy of RBFNs will be described in the following section.

A. ***Network Architecture of Radial Basis Function Networks***

Here, Radial Basis Function Networks (RBFNs), an intelligent system of Artificial Neural Networks (ANNs) is used in this study. It consists of three layers; the input layer, hidden layer and output layer.

A Radial Basis Function Network (RBFN) is a hybrid learning neural network. It is a two-layer fully-connected network with an input layer which performs no computation as shown in Fig. 2.

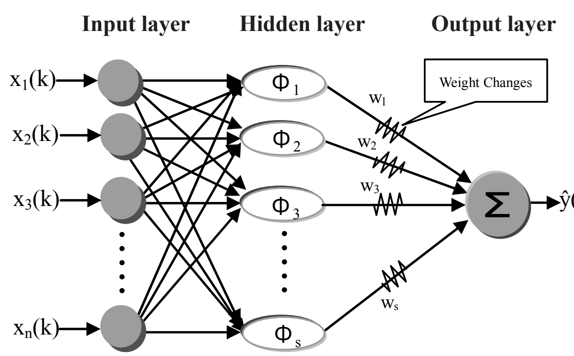

Fig. 2 The Architecture of RBFNs Model

The hidden layer: Learning in the hidden layer is performed by using an unsupervised method, the K-means algorithm. The activation function of the hidden nodes is radially symmetric in input space; the magnitude of the activation given a particular record is a decreasing function of the distance between the input vector of the record and the center of the basis function. The distance metric employed is the Euclidean distance. The activation of the hidden neuron i with presented pattern s has the form:

$$\phi_s(i) = \exp\left(-\frac{\|s-c_i\|^2}{2\sigma_i^2}\right) \qquad (1)$$

Each hidden unit has an associated σ'width' value which defines the nature and scope of the unit's receptive field response. It is equivalent to the standard deviation of the width of the Gaussian response, so larger values allow more points to be included.
The output layer: Learning in the output layer is performed by computing a linear combination of the activation of the basis functions, parameterized by the weights, w between hidden and output layers. For the output k of record s as $o_k(s)$, where j describes the j^{th} hidden neuron, i.e. the j^{th} center, the number of centers being m, we can obtain the predicted output :

$$o_\kappa(s) = \sum_{j=1} w_{jk} \times \phi_s(j) \qquad (2)$$

The weights w_{jk} are initialized to small random values (between−0.001 and 0.001). These operations are repeated until the maximum number of iterations fixed is reached or until the prediction error ek is less than a given threshold and finally output is obtained by the sum of $o_k(s)$ as expressed ŷ(k). [2)]

B. ***Characteristics and Learning Strategy of Radial Basis Function Networks***

RBFNs have static Gaussian function as the non-linearity for the hidden layer processing elements. The Gaussian function responds only to a small region of the input space where the Gaussian is centered. The key to a successful implementation of these networks is to find suitable centers for the Gaussian

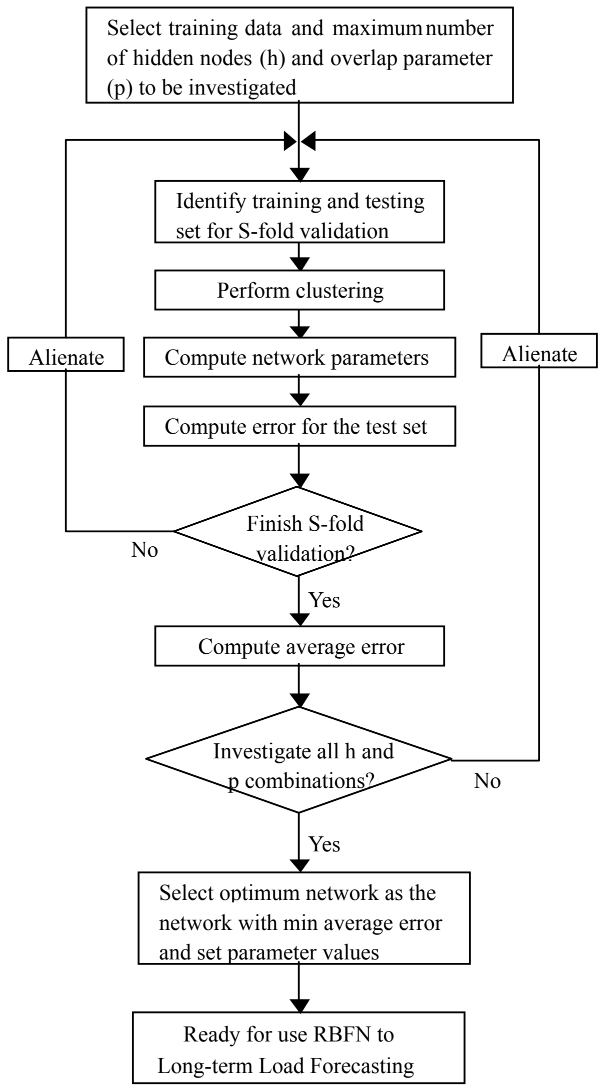

Fig. 3 Flowchart of RBFN and Its Learning Strategy

functions. This can be done with supervised learning, but an unsupervised approach usually produces better results. For this reason, Neuro Solutions implements RBFNs as a hybrid supervised-unsupervised topology.

Here Fig. 3 shows the learning strategy of RBFN and the optimization of Long-term Load forecasting. The design parameters, that is the number of Radial Basis Function units in the hidden layer (h) and the value of the overlap parameter (p) for the nearest neighbor are chosen by the model builder to attain the optimal network structure for better performance. The parameters can be easily determined using a method called the S-fold cross validation procedure (SFCV). The simulation starts with the training of an unsupervised layer. Its function is to derive the Gaussian centers and the widths from the input data. These centers are encoded within the weights of the unsupervised layer using competitive learning. During the unsupervised learning, the widths of the Gaussians are computed based on the centers of their neighbors. The output of this layer is derived from the input data weighted by a Gaussian mixture.

Once the unsupervised layer has completed its training, the supervised segment then sets the centers of Gaussian functions (based on the weights of the unsupervised layer) and determines the width (standard deviation) of each Gaussian. Any supervised topology (such as a Multi-Layer Perceptron) may be used for the classification of the weighted input.

The advantage of the RBFNs is that it finds the input to output map using local approximators. From the characteristics of RBFNs, we perceived that it is possible to obtain a better solution for prediction type problem with a large number of inputs. In long-term load forecasting, it is usually used a huge quantity of data which is suitable for RBFNs architecture. Thus, RBFNs is proposed for long-term load forecasting.

4. The Maximum Electric Power Demand Prediction with the Present Power System Structure

Japanese electric power demand has steadily increased, however, the load factor of total power system has decreased. This trend will certainly continue in the future and it is very important though difficult for the electric companies to supply electricity in a secure and economic manner. Here, a prediction method, RBFNs that trains faster and leads to better decision boundaries is presented to forecast maximum electricity demand.

Here the simulation was held to check the validity of the network by taking the actual data for learning from the years 1975 to 2000 for all those economy factors. The years 2001 to 2030 had been taken as target years to predict the maximum electric power demand which is compared with other traditional method of ANNs named Back Propagation (BP). Figure 4 shows the maximum electric power demand up to the year 2030.

The error calculation of RBFN is shown in Table 1. Here validation as well as training years is taken from the year 1975 to 2000 and target years (average test) are taken from 2001 to 2030. It shows the training error is 1.150% and the target error is calculated for those certain years are 5.752% at an average, whereas from BP we obtained the error is 8%.

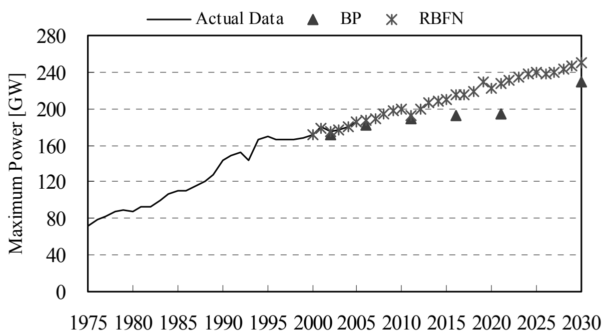

Fig.4 Forecasting the Peak Loads from 2001 to 2030

Table 1 Output Error Measures of RBFNs

	Root Mean Squared Error	**Mean Absolute Squared Error**	**Mean Absolute Error [%]**
Training (1975~2000)	0.138	0.117	1.150
Average Test (2001~2030)	5.016	4.909	5.752*

*Average error obtained by BP is 8%

5. Restructuring Power Systems Based Maximum Electric Power Demand Prediction Structure

Japan has regulated entry into its electricity industry since 1951. Since then, the regulators have approved nine vertically integrated electricity companies as regional monopolies. As a result, Japanese companies charge much higher electricity prices than those in the US and Europe do. There are many controversial points concerning differences in the lifestyles and the tariff systems among countries, as well as those about choice of conversion factors, for fair international comparison of charges. Deregulation has the potential to significantly lower electricity prices in Japan, which differed from Germany's by at least 17 percent and, in the extreme case, from that of the US by 68 percent in 1997. [3)]

The maximum electric power demand in Japan is increasing, but the rate is comparatively decreasing every 10 years. Table 2 shows the trend of maximum power increasing rate from the 1975 to 2000.

Table 2 Transition of the Annual Average Load Increasing Rate (from actual data)

Period (Years)	Average increasing rate
1971~1980	6.5%
1981~1990	5.4%
1991~2000	1.7%

A. *Necessity of Renewable Energies to Sustain Stable Power Flow and Simulation Results*

According to the observation of the task force of Central Research Institute of Electric Power Industry (CRIEPI), Japan, the general image of the electric power system growth of Japan in the middle of the 21st century is that it will be saturated. The main results of its investigation can be outlined in the following three points.

- Regarding the future energy consumption, it is estimated that the demand growth will become gradually saturated within approximately 1.5 times that of the present by the middle of the 21st century.
- The total installed generation capacity required for the supply at that time will be about 300 GW.
- According to the demand growth, the electric power system will need to be enlarged to 1.5–2.0 times that of existing systems by the adoption of the power system enhancement measures such as the power electronics technologies, including FACTS (Flexible AC Transmission Systems) and advanced HVDC (High Voltage DC) systems.

Regarding the electric power demand in the future in Japan, it is generally thought that the share of electrical energy in the industrial sector may decrease as industries get more software and become more information oriented. On the contrary, the share will surely expand in the residential and commercial sector due to further amenities, health, and social welfare as the lifespan of people is increasing. The task force set the following as the basic points of view. In the 21st century, further abundance may be expected for everyone with qualitative changes in the end-use structure. It is estimated that the population will reach its peak a little before year 2020 and then gradually decrease, according to the data from National Institute of Population and Social Security Research. As a result, the electric demand in Japan will reach and be saturated at the maximum of approximately 1.5 times of its present demand between 2030 and 2050.

The amount of electricity generated to meet this estimated demand will reach approximately 1,300 TWh, whereas, the value of the annual peak demand at the saturated point is estimated to be about 250 GW.

- Nuclear plants are to be increased to 70 GW (+30 GW).
- Natural or renewable energies, including pumped storage hydro plant, will be 60 GW (+20 GW).
- Thermal plants become 150 GW (+30 GW).

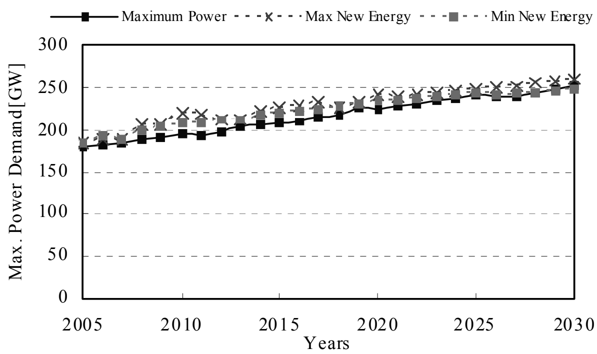

Fig. 5 Forecasting Maximum Electric Power Demand Introducing Renewable Energies.

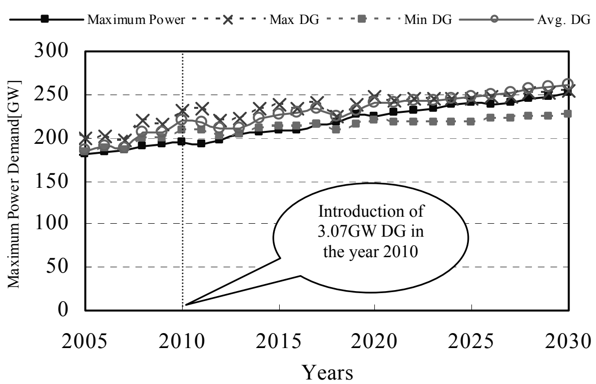

Fig. 6 Forecasting max power demand introducing DG5).

Table 3. An Estimation of Introducing the Distributed Generations in 21st Century[4].

Type	Estimation	Capacity (MW)
IPP	15-20% of potential capacity 38 to 52GW (Fundamental Policy Subcommittee in Electric Power Utility Committee, 1997)	2400 to 2600
Cogeneration, except for FC	Around 20% of the total capacity increased at a constant rate from now	2400 to 2800
Waste generation	Increased at a constant rate from now	6000 to 6500
Photo voltaic generation	20-30% of potential capacity 130-190 GW	28000 to 45000
Fuel cell generation	To be increased more than 3 times cogeneration	7000 to 8800
Wind generation	Estimation from site situation	330 to 360
Energy storage	Half of increased capacity required to be optimally introduced to power system	6650
Power Supply Capability	(kW value is taken account on variable output generation)	35700 to 45300

Some parts of the large-scale generation plants will change to small-scale dispersed ones by the middle of the century. Furthermore, addressing the introduction of dispersed generations such as Independent Power Producers (IPP) and cogeneration to lower voltage power networks as distributed generation (DG), power electronics technologies are essential, not only for power flow, voltage control, and power system stabilization but also for power quality improvement of harmonics and voltage disturbances.

Figure 5 shows the forecasting result when new energies (cogeneration, waste generation, photovoltaic generation, wind power generation, fuel cell) with IPPs penetration are expected as shown in Table 3. The simulation results shows that the maximum power demand goes higher introducing renewable energies.

Figure 6 shows the simulation result of maximum power demand after introduction of DG about 3.07 GW provided by EDMC.[5] It is anticipated that the demand will increase in maximum penetration of DG; whereas, minimum penetration of DG shows a decreasing trend after the year 2017. It can be illustrated that the demand will be saturated in 2017 provided by minimum introduced DGs.

Table 4 Measuring of Maximum Electric Power Demand Increasing Rate up to 2030

Years	Average maximum power demand increasing rate
1971~1980	6.5%
1981~1990	5.4%
1991~2000	1.7%
2001~2010	0.9%
2011~2020	1.2%
2021~2030	1.1%

Table 5 Measures of Error Obtained by RBFNs for Forecasting Maximum Electric Power Demand up to the Year 2030

Types of error Data	Root Mean Squared Error	Mean Absolute Squared Error	Mean Absolute Error [%]
Training as well as Validation (1975~2000)	4.93	3.42	**2.09**
Average Test (2001~2030)	8.57	8.39	**3.44 ***

*Overall test error by BP is obtained about 14.19%

Some reports illustrate that the rate of maximum power demand in Japan will decline; however, the present study shows that the maximum value of the electric power demand up to the year 2030 will be 250.90GW. We obtained the incremental rate of maximum electric power demand for every 10 years up to the year 2030 by calculation as shown in Table 4.

This result is calculated from the forecasted results of maximum electric power demand for each individual year up to 2030. It is shown from the actual data that the rate was more than 5% from the year 1971 to 1990, whereas, the rate is decreased rapidly from the year 1991 to 2030 comparing to the previous years. The lowest increasing rate is 0.9% between the years 2001 and 2010. And for the last 10 years, it shows about 1.12%. So, the increasing rate is not so high compared to the previous years and we assume the rate will be saturated by the year 2050 and decrease afterwards.

It can be easily seen how investment is necessary for new construction of power plants from this forecasted results for future years. In the obtained forecasted results the training error is suppressed within 3% and the overall test error shows less than 5% which is a big contribution compared to the previous results obtained by BP. Though the parameters and centers setting of the RBFN model is quite tough to find out the best set, it is obtained by trail and error method considering the least prediction error for all the networks.

These fluctuations in long-term loads may bring this question that we may not be able to forecast the loads for very long periods. The answer to this question is to provide a sense of security to the power companies, a sensitivity analysis for load deviations and many variables, which may cause these fluctuations. That means, we must not only rely on the forecast of very long period, but also consider that as a reference or rough forecasting and then correct our forecasted curves by new coming information. This new coming information may come from the newly observed data taken monthly or yearly or may come from the results of existing simulations. Thus we can use newly obtained data and update the forecasted loads, which have been predicted already. In this study, the measures of output error of RBFNs are shown in Table 5.

6. Conclusions

As power deregulation has already started in Japan, in this study we considered two cases: predicting the maximum electric power demand both before and after restructuring the power systems. Considering these results, it is possible to minimize the loss of the extra generation including costs. Further case studies will be required for variations of the new environment that is taken into account in this study.

It is not easy to set up a new power plant within a very short period. It takes about 7 to 10 years to construct a big power generation. For this reason, it is highly necessary to meet the increasing load demand in the near future using another source of power generation, renewable energies such as solar power, wind power, biomass, and micro hydro power that are easily constructed compared to building a large power plant.

So, the following issues are under consideration for future studies.

- Prediction of load demand introducing renewable energies in the power system of a region.
- Forecasting the electricity demand considering power deregulation.
- The whole power system network can be considered as decentralized and reconfigure those as small power systems network for whole Japan for future. It is necessary to simulate the whole small-grid (mini or micro- grid) system to evaluate whether they are economical or not, including the case of reliability.
- Applying sensitivities analysis of input changes of more than two or three parameters at a time and considering new inputs related to new energies, such as the actual and forecasted amount of renewable energies, CO_2, number of air-conditioners, number of mobile phones, etc.
- Considering various scenarios for long-term load forecasting with changing environment regarding power deregulation or other new issues.

Ultimately, for future study, we are considering the necessary countermeasures for the problem of load saturation for the 21st century. We believe that the results of this study will be useful for other country's power companies.

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