Estimation of Changes in the Electricity Demand Curve under the State of Emergency

Estimation Using an Artificial Neural Network (ANN)

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Abstract

Governments around the world have taken powerful measures to counter the spread of the new coronavirus (Covid-19), such as requesting voluntary restraint of economic activity and imposing city-wide lockdowns, causing enormous economic damage and a major decline in energy demand as a result. The Japanese government declared a state of emergency following a stay-at-home advisory as Covid-19 spread. This report analyzes the impact of Covid-19 and the state-of-emergency declaration on Japan's energy demand, focusing on the impact on hourly electricity demand. In the analysis, we use the artificial neural network developed by the IEEJ to obtain estimates that take into account the air temperature and other meteorological conditions, and compare these estimates with the actual values to determine the change in the electricity demand curve.

The analysis shows that the electricity demand declined by an estimated 3.8% in April and 9.5% in May in the Tokyo area. The impact of the declaration on the decline in demand varied by region but tended to be greater in metropolitan areas where the number of cases was high. The impact also varied by hour of day, presumably reflecting regional industrial structures.

1. Introduction

Governments around the world have taken powerful measures to counter the spread of the new coronavirus (Covid-19), such as requesting voluntary restraint of economic activity and imposing city-wide lockdowns, causing enormous economic damage. Accordingly, energy demand declined sharply in a wide range of sectors as economic activity declined and more people stayed home due to city-wide lockdowns. Japan declared a state of emergency on April 7 for seven prefectures, namely Tokyo, Saitama, Chiba, Kanagawa, Osaka, Hyogo, and Fukuoka as Covid-19 spread, placing self-imposed restrictions on a wide range of activities. As the declaration was subsequently expanded to include all prefectures on April 16, the spread of Covid-19 and the resulting decline in economic activity significantly affected the demand for energy in Japan.

As examples of the reported impact of Covid-19 on electricity demand, Abiko (2020)[1] found that demand declined by just under 10% compared with other years in the TEPCO power grid area as of late April. Further, the Agency of Natural Resources and Energy (ANRE) (2020)[2] reported that the demand for April 2020 declined by 1.1–9.2% year-on-year (by 4.2% for the Tokyo area) and by 1.1–5.0% year-on-year (4.0% for the Tokyo area), with

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[1] Naoto Abiko (2020). The impact of Covid-19 on electricity demand. https://www.mri.co.jp/knowledge/mreview/202006-1.html

[2] Agency for Natural Resources and Energy (2020), Matters related to electricity demand. https://www.meti.go.jp/shingikai/enecho/denryoku_gas/denryoku_gas/pdf/025_07_00.pdf

and without adjustment for meteorological conditions, respectively. Moreover, in the Electric Daily News [3] newspaper dated June 11, 2020, the Japan Weather Association noted that weekday demand was around 10% lower than the past few years even when considering temperature differences, and attributed the decline to the slump in and voluntary restraints on corporate activity. When analyzing the impact of Covid-19 and the resulting state-of-emergency declaration on electricity demand, it is essential to adjust for temperature and other meteorological conditions. Abiko based his estimate on the daily average temperatures during the past three years and the daily electricity demand for the same period, while the Japan Weather Association plotted an approximate curve based on the relationship between the daily average temperature and demand using the data for the past five years, and used it for analysis. It is not known how the ANRE adjusted their data based on meteorological conditions.

This report analyzes the impact of the spread of Covid-19 and the state-of-emergency declaration on Japan's energy demand, focusing on the impact on hourly electricity demand. In the analysis, we use the artificial neural network developed by the IEEJ to obtain estimates that take into account the air temperature and other meteorological conditions, and compare these estimates with the actual values to determine the change in the electricity demand curve caused by the declaration.

2. Estimation method and data used

2-1 Estimation method: Electricity demand curve estimation model using artificial neural network (ANN)

We used an electricity load estimation model that uses an artificial neural network (ANN) in order to project the impact of the state-of-emergency declaration by plotting the electricity demand curves without the impact of Covid-19 or the declaration, and comparing it with the actual electricity demand values. ANN is one of the most frequently used means of machine learning in recent years and has been used in many published studies for forecasting electricity demand. The ANN creates a forecast model by "learning" numerous pairs of past input data and output data; by entering a new input data into the model, a corresponding output data is generated. We used the following data for our model (see Appendix 1 for details).

Input data: Calendar data (year, month, day, day of week, and whether the day is a holiday) and meteorological data (air temperature, rainfall, and 24-hour solar radiation)
Output data: electricity demand (24-hour value)

We estimated the change in electricity demand associated with the state-of-emergency declaration by first making the model learn the situation before Covid-19 using the input and output data from January 1, 2012 to March 1, 2020, then entering the input data after the spread of Covid-19 into the model to generate output data for up to May 31, 2020, and comparing the output data with the actual data. We used the same model as in past reports[4,5], but with modifications (see Appendix 2 for details).

[3] Electric Daily News, Demand falls 10% due to Covid-19, June 11, 2020

[4] Yuji Matsuo, Kimiya Otani, Tomofumi Shibata, Yasuo Yorita, Yasuaki Kawakami, Yu Nagatomi (2018). Short-term electricity demand forecasting using artificial neural network ―Study on 10 cities in Japan―. http://eneken.ieej.or.jp/data/8106.pdf

[5] Tomofumi Shibata, Kimiya Otani, Yasuo Yorita, Yasuaki Kawakami, Yu Nagatomi, Yuji Matsuo (2019). Evaluation of Factors Influencing the Accuracy of Electric Demand Forecasting by Artificial Neural Networks: Effect of Changes in Model Configuration, Journal of Japan Society of Energy and Resources, 40(5), pp. 144–153.

2-2 Data used

We conducted the analysis for each area of the 10 Japanese power transmission and generation utilities as with past reports. The calendar data (year, month, day, day of week, and whether the day is a holiday) of that day and the meteorological data (air temperature, rainfall, and 24-hour solar radiation) were used as input data, and the electricity demand (24-hour) was analyzed as output data. This allowed us to incorporate the calendar data and meteorological data into the electricity demand analysis. By comparing estimates that reflect the temperature and other meteorological conditions with the actual data, we were able to analyze the impact of the expansion of Covid-19 and the state-of-emergency declaration more accurately.

The outline and sources of data used are described in Appendix 1.

3. Evaluation results

3-1 Comparison by area

The evaluation results for each region are described below. The results for the Tokyo area, as a representative region, and the Chubu area, which saw the greatest fall in electricity demand, are described in detail. Then, the results for all areas are compared horizontally in the next section.

3-1-1 Tokyo area

The Tokyo area has had the highest number of Covid-19 cases in Japan and residents had been advised to stay home since before the state of emergency was declared. This area also has the highest electricity demand in the country, with particularly high demand in the business sector for offices and commercial facilities, and is thus expected to be affected strongly by a stay-at-home advisory.

The evaluation showed that the change in Tokyo's electricity demand for April (trend of actual and estimated values) was not large before the declaration (Fig. 3-1). However, the gap between the values began to widen from April 7 when a state of emergency was declared, widening further toward the latter half of April (Fig. 3-2). This suggests that the impact on electricity demand grew from this point due to close compliance with the stay-at-home advisory, closure of retailers and restaurants, and temporary suspension of manufacturing following the declaration.

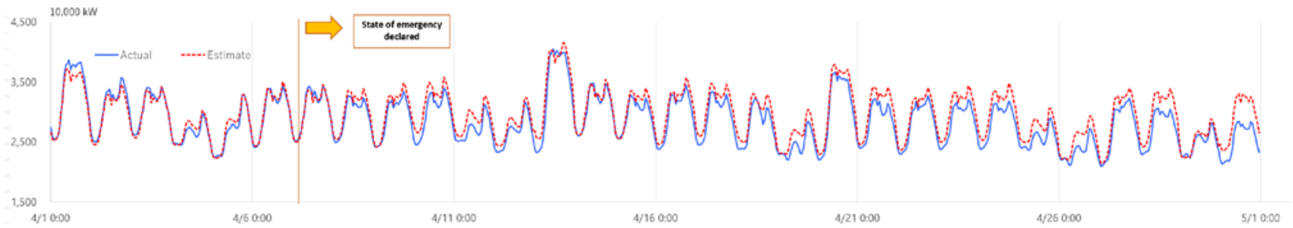


Fig. 3-1 Electricity demand of Tokyo area (trend of actual and estimated values) (April)

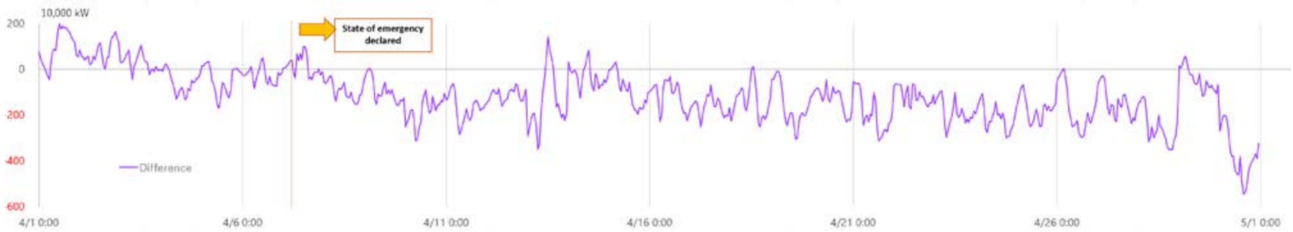


Fig. 3-2 Electricity demand of Tokyo area (difference between actual and estimated values) (April)

The gap between estimated and actual values grew further from the start of May, and electricity demand was greatly reduced during the “Golden Week” holidays (Fig. 3-3, Fig. 3-4). It is considered that people voluntarily refrained from leisure activities due to the stay-at-home advisory and that the cancellation of events during the holidays significantly limited people’s activities in the Tokyo area, reducing electricity demand. The electricity demand remained low after the holidays ended, as the voluntary restraint on activities continued after the holidays due to the extension of the declaration till May 31, which was announced on May 4. Then, after it was announced that the declaration would be lifted on May 25 for the Tokyo area, the chart shows that the decline in electricity demand shrank around late May as people expected that the declaration would be lifted before it actually was.

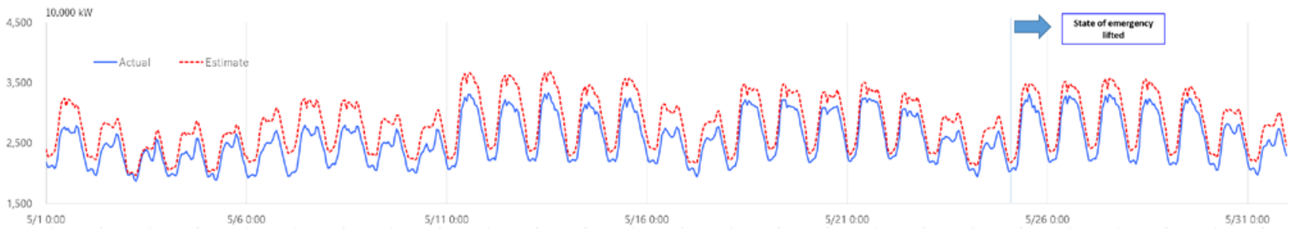


Fig. 3-3 Electricity demand of Tokyo area (trend of actual and estimated values) (May)

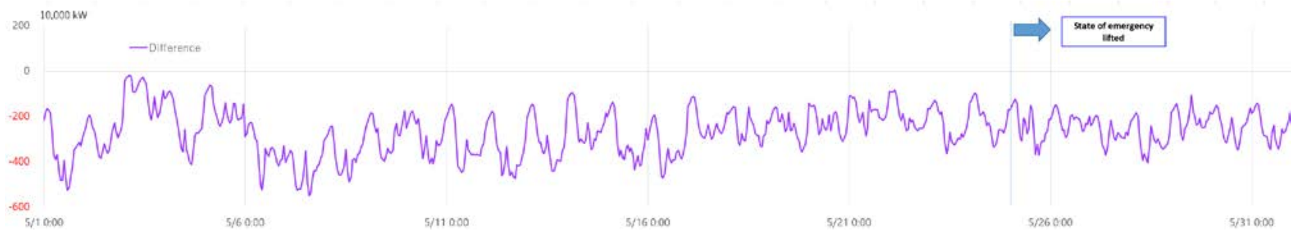


Fig. 3-4 Electricity demand of Tokyo area (difference between actual and estimated values) (May)

As described above, Tokyo’s electricity demand began to fall particularly after the state of emergency was declared, and the decline grew till the end of the Golden Week holidays that started at the end of April. The decline then gradually decreased toward the lifting of the declaration. The decline in Tokyo’s electricity demand was estimated to be approx. 3.8% versus the estimated value for April and approx. 9.5% for May (Tables 3-2 and 3-3).

3-1-2 Chubu area

In the Chubu area, the number of cases soared in the initial stage of the spread of Covid-19 in Japan. Aichi prefecture, the area’s largest, declared a state of emergency on its own on April 10. The area is home to the auto industry and aircraft-related manufacturing, and therefore industry accounts for a large portion of electricity demand.

The evaluation showed that for Chubu’s electricity demand for April (trend of actual and estimated values), the gap between the actual and estimated values began to grow gradually before the state of emergency was declared (Fig. 3-5). The gap widened further with the expansion of areas covered by the state of emergency on April 16 to include the Chubu area, widening even more toward the latter half of April (Fig. 3-6). Accordingly, Chubu’s electricity demand declined throughout April since before the declaration due to Aichi prefecture’s unique initiatives and the decline in industrial activity as a whole, including that of domestic and international manufacturing supply chains. The impact on electricity demand then increased toward the Golden Week holidays as more retailers and restaurants closed, in addition to the manufacturing sector.

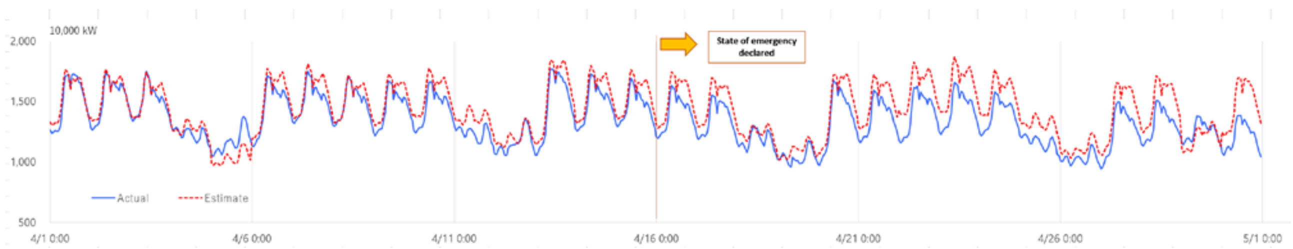


Fig. 3-5 Electricity demand of Chubu area (trend of actual and estimated values) (April)

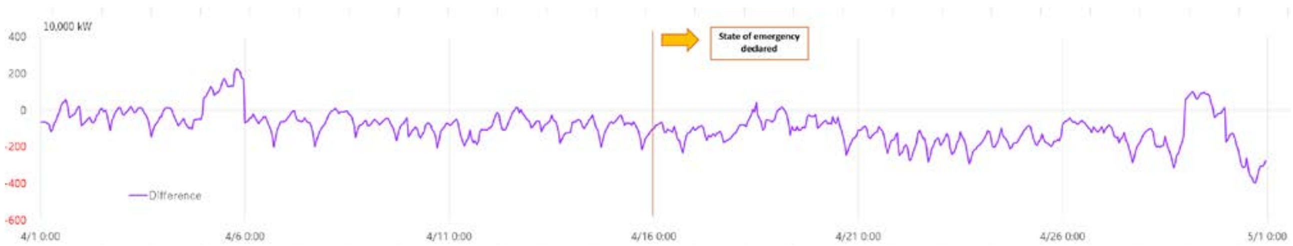


Fig. 3-6 Electricity demand of Chubu area (difference between actual and estimated values) (April)

In May, the gap between estimated and actual values grew wider than in April, indicating that electricity demand dropped significantly during the Golden Week holidays (Figs. 3-7 and 3-8). It is considered that people voluntarily refrained from leisure activities due to the stay-at-home advisory, and that the cancellation of events during the holidays significantly limited people's activities in the Chubu area and reduced electricity demand, as happened in the Tokyo area. Although an extension of the declaration till May 31 was announced on May 4 during the holidays, the pace of decline of the Chubu area's electricity demand slowed gradually from the end of the holidays due to speculation that the declaration would be lifted earlier. Then, when the declaration was lifted on May 14, the fall in electricity demand shrank toward late May.

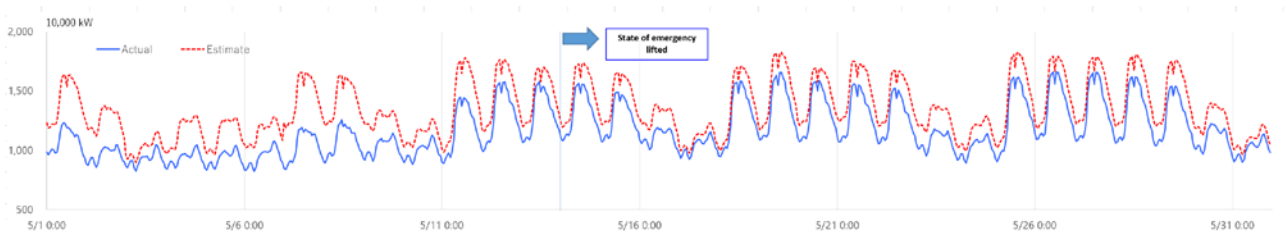


Fig. 3-7 Electricity demand of Chubu area (trend of actual and estimated values) (May)

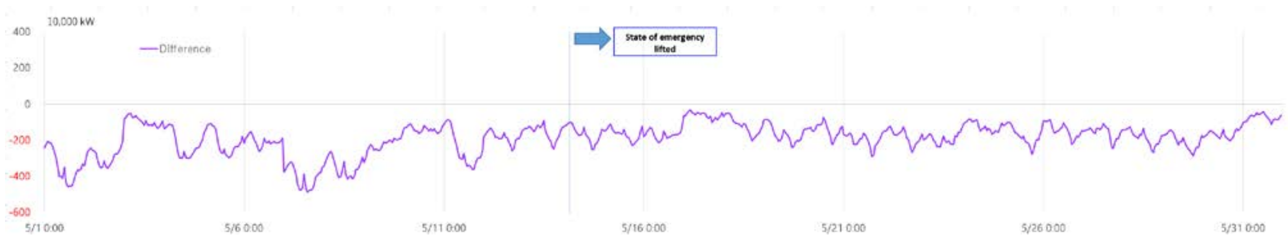


Fig. 3-8 Electricity demand of Chubu area (difference between actual and estimated values) (May)

As described above, Chubu's electricity demand began to fall before the state of emergency was declared, and the decline grew till the end of the Golden Week holidays that started at the end of April. The decline then gradually narrowed toward the lifting of the declaration immediately after the holidays. The decline in Chubu's electricity demand was estimated to be approx. 6.4% versus the estimated value for April and approx. 14.0% for May (Tables

3-2 and 3-3).

3-1-3 Comparison of full-day demand curves of the Tokyo and Chubu areas

The analysis showed that electricity demand declined in both the Tokyo and Chubu areas mainly due to the impact of the state-of-emergency declaration. The Chubu area saw a larger drop in electricity demand compared to other areas and therefore is considered to have been hit hard by the stay-at-home advisory and impact on industry associated with Covid-19.

Regarding changes in the electricity demand curves, we compared the hourly electricity demand during the state of emergency against estimated values assuming there was no declaration. The result showed that the impact on electricity demand varied by hour of day, with Tokyo having a relatively flat curve with a 5–10% decrease while Chubu slumped by over 15% at around 17:00 (Fig. 3-9). Since this analysis was conducted using macro electricity demand data for the entire area, it is difficult to analyze the hourly change in electricity demand by sector or by region within an area. One theory for the differences by sector is that the Chubu area’s overall hourly demand may be affected to a greater extent by changes in demand in the industrial sector than in other areas due to the higher ratio of demand from manufacturing in electricity demand, in addition to the impact of the closure of retailers and restaurants which may occur in other areas as well.

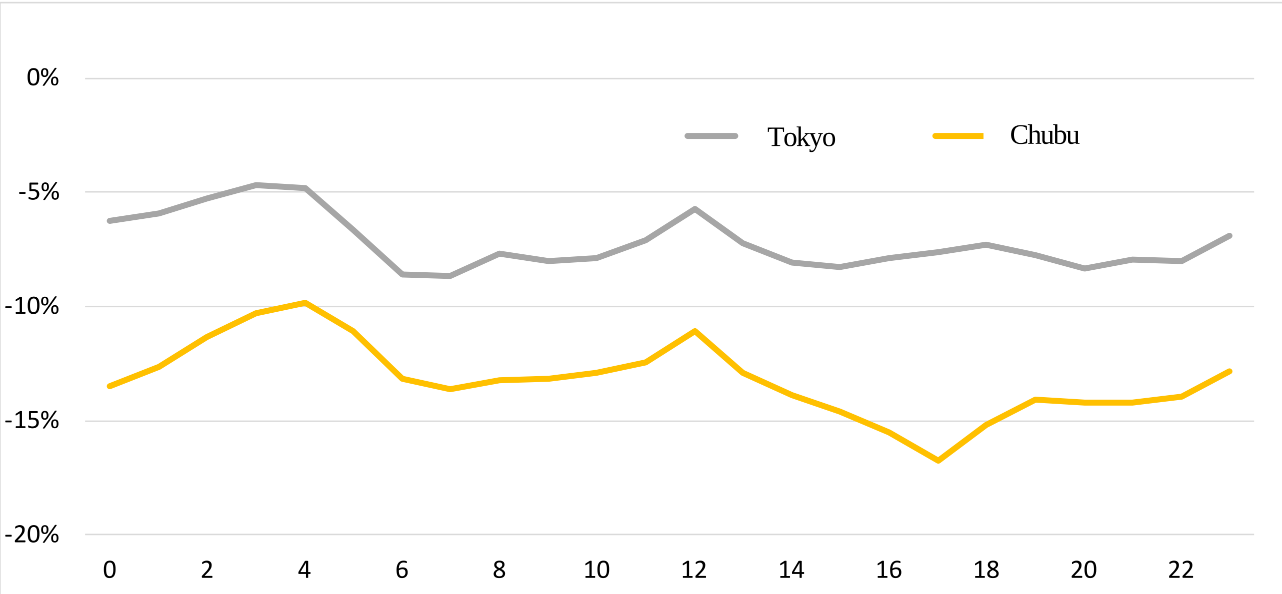


Fig. 3-9 Hourly difference in actual and estimated electricity demand during the state of emergency (Tokyo and Chubu areas)

3-2 Comparison among areas

This section compares the monthly analysis results among the areas to clarify the differences between regions and the changes in impact with the progress of Covid-19 countermeasures, including the state-of-emergency declaration.

3-2-1 Electricity demand in March

A state of emergency had yet to be declared in March although the number of Covid-19 cases was increasing in major cities and Hokkaido. The impacts on economic activity and electricity demand were caused mainly by each municipality’s initiatives and advisories to stay home and close businesses during this period. The impact on electricity demand was relatively minor but was somewhat greater in the Tokyo and Kansai areas compared to other areas.

Table 3-1 Average electricity demand for March (in 10,000 kilowatts)

	Actual value	Estimated value	Difference ratio	(Reference) Result for 2019
Hokkaido	367	367	0.0%	370
Tohoku	950	962	−1.2%	977
Tokyo	3,167	3,209	−1.3%	3,195
Chubu	1,507	1,521	−0.9%	1,556
Hokuriku	341	341	0.0%	351
Kansai	1,588	1,620	−2.0%	1,662
Shikoku	304	302	0.7%	308
Chugoku	674	681	−1.0%	690
Kyushu	931	940	−0.9%	949
Okinawa	77	78	−0.9%	76

Source: All actual values for 2019 in this article have undergone day-of-week adjustments relative to 2020.

3-2-2 Electricity demand in April

A state of emergency was declared on April 7 in seven prefectures and was expanded to all prefectures on April 16, requiring the nationwide implementation of countermeasures and extensive staying at home. As a result, the gap in impact on demand between regions grew compared to March, with Chubu, Kansai, and Okinawa showing greater falls.

Table 3-2 Average electricity demand for April (in 10,000 kilowatts)

	Actual value	Estimated value	Difference ratio	(Reference) Result for 2019
Hokkaido	325	330	−1.6%	323
Tohoku	876	879	−0.3%	873
Tokyo	2,853	2,966	−3.8%	2,910
Chubu	1,346	1,439	−6.4%	1,386
Hokuriku	314	319	−1.6%	312
Kansai	1,453	1,528	−4.9%	1,493
Shikoku	282	281	0.2%	275
Chugoku	615	603	2.0%	616
Kyushu	860	879	−2.2%	862
Okinawa	74	78	−5.2%	82

3-2-3 Electricity demand in May

In May, electricity demand fell significantly in all areas during the Golden Week holidays as leisure-related economic activity shrank due to stay-at-home advisories during the holidays. The state-of-emergency declaration began to be lifted in phases starting on May 14 and was lifted completely on May 25, including in the four remaining prefectures of Tokyo, Kanagawa, Chiba, and Saitama. Nationwide, electricity demand plummeted during the holidays but the fall gradually shrank after the holidays due to widespread expectation that the state of emergency would be lifted. Of the regions, Chubu, Kansai, and Chugoku experienced relatively large declines.

Table 3-3 Average electricity demand for May (in 10,000 kilowatts)

	Actual value	Estimated value	Difference ratio	(Reference) Result for 2019
Hokkaido	285	297	4.3%	295
Tohoku	757	826	−8.4%	815
Tokyo	2,553	2,822	−9.5%	2,848
Chubu	1,162	1,352	−14.0%	1,355
Hokuriku	258	286	−9.9%	288
Kansai	1,296	1,462	−11.4%	1,456
Shikoku	256	267	−4.3%	265
Chugoku	529	593	−10.8%	585
Kyushu	790	848	−6.8%	855
Okinawa	84	91	−7.5%	87

Based on these results, a time-based observation of changes in regional electricity demand shows that electricity demand declined significantly in the metropolitan areas of Tokyo, Chubu, and Kansai due to the impact of the state of emergency and others (Fig. 3-10). Covid-19 countermeasures including the impact of the state of emergency on electricity demand varied among regions depending on their industrial structure and meteorological conditions. Going forward, in restarting economic activity while containing the spread of Covid-19, a shift to “new lifestyles” is being recommended. The impact of this shift on electricity demand deserves attention.

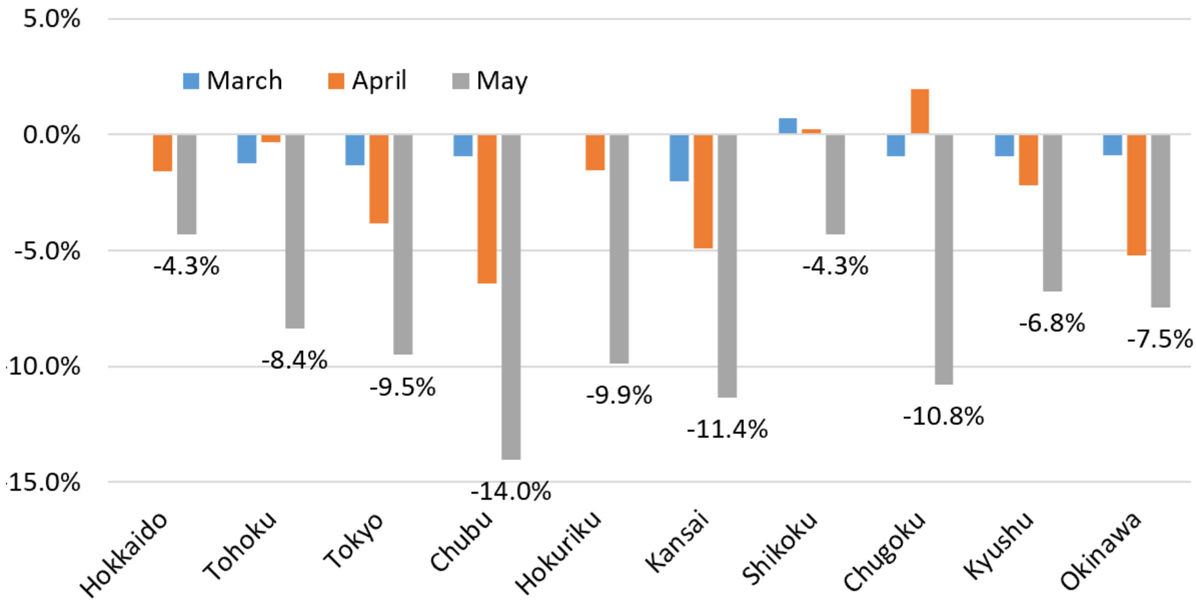


Fig. 3-10 Difference between estimated and actual values (average of each month)

3-2-4 Comparison of full-day demand curves of the 10 areas

Based on the analysis in Section 3-1-3, the difference between the full-day demand curve from the full-day average is illustrated in Fig. 3-11. The figure shows that the curve tends to be positive in the early morning as the fall in demand is smaller than the full-day average, but becomes larger toward the evening and falls below average, resulting in a greater fall in demand. This indicates that the fall in demand is greater during times of the day with more human activity. Further, Section 3-1-3 noted that the Chubu area saw a particularly large fall in demand around 17:00, but a comparison of the 10 areas shows that Chugoku and Shikoku also saw large falls at the same time of day.

By analyzing changes in electricity demand due to the state-of-emergency declaration in more detail on an hourly basis as in this study, in addition to on a monthly basis, the impacts of the state-of-emergency declaration, voluntary quarantines, and new lifestyles including teleworking can be analyzed in more detail.

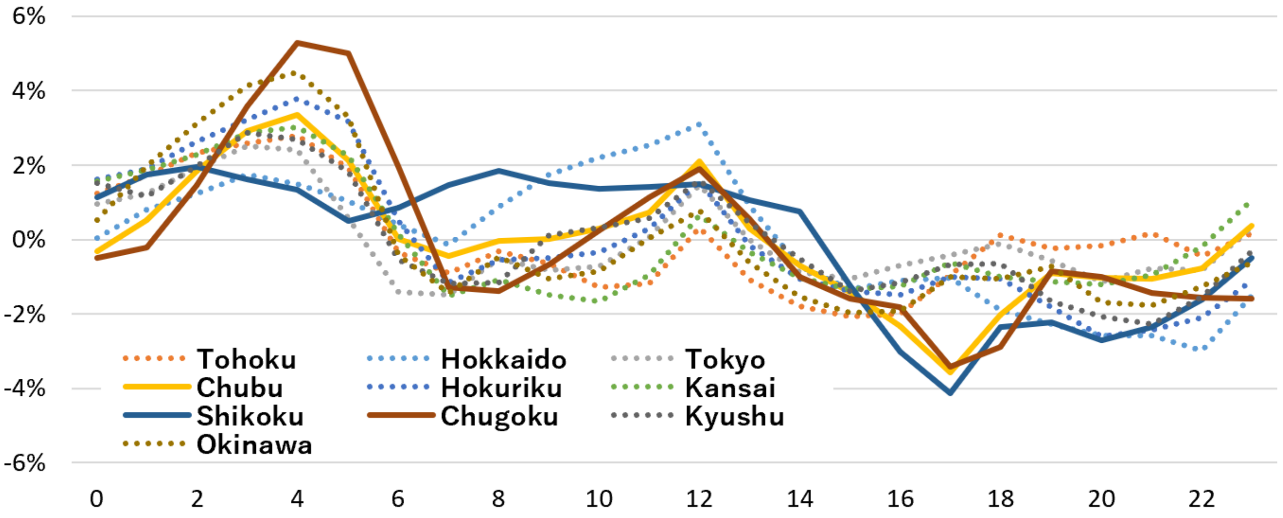


Fig. 3-11 Difference between the hourly demand curve from the full-day average during the state of emergency

4. Conclusion

This report analyzed the impact of the spread of Covid-19 and the state-of-emergency declaration on Japan's energy demand, focusing on the impact on hourly electricity demand. We used the artificial neural network developed by the IEEJ to obtain estimates that took into account the air temperature and other meteorological conditions, and compared these estimates with the actual values to determine the change in the electricity demand curve caused by the declaration.

The analysis showed that the impact of the state of emergency on electricity demand varied by region but tended to be greater in metropolitan areas with larger numbers of cases. Further, the impact also varied by hour of day, presumably reflecting regional industrial structures. The recovery of decline in demand showed signs of easing with the lifting of the declaration, but the hourly electricity demand is expected to follow a new pattern as quarantines associated with the state of emergency and the resulting "new lifestyles" take root, along with awareness of the possibility of second and third waves of Covid-19.

Appendix 1 Details of the data used

The following data was used.

- Calendar data (year, month, day, day of week, whether the day is a holiday)
- Meteorological data (air temperature, rainfall, and 24-hour solar radiation): created based on the Japan Meteorological Agency website
- Electricity demand (24-hour values): Created from disclosed data of general power transmission and distribution companies

Appendix Table 1-1 Electricity demand analysis data

Area	Data acquisition period	Data Number of days	Data Days without data
Hokkaido	2012/1/1 – 2020/5/31	3,038	36
Tohoku	2012/1/1 – 2020/5/31	2,610	464
Tokyo	2012/1/1 – 2020/5/31	3,045	29
Chubu	2012/1/1 – 2020/5/31	3,035	39
Hokuriku	2012/1/1 – 2020/5/31	3,067	7
Kansai	2012/1/1 – 2020/5/31	3,066	8
Shikoku	2012/1/1 – 2020/5/31	3,065	9
Chugoku	2012/1/1 – 2020/5/31	3,067	7
Kyushu	2012/1/1 – 2020/5/31	3,069	5
Okinawa	2012/1/1 – 2020/5/31	1,978	1,096

Source: Created based on websites and disclosed data of utilities. Missing data is due to errors in the data recording stage.

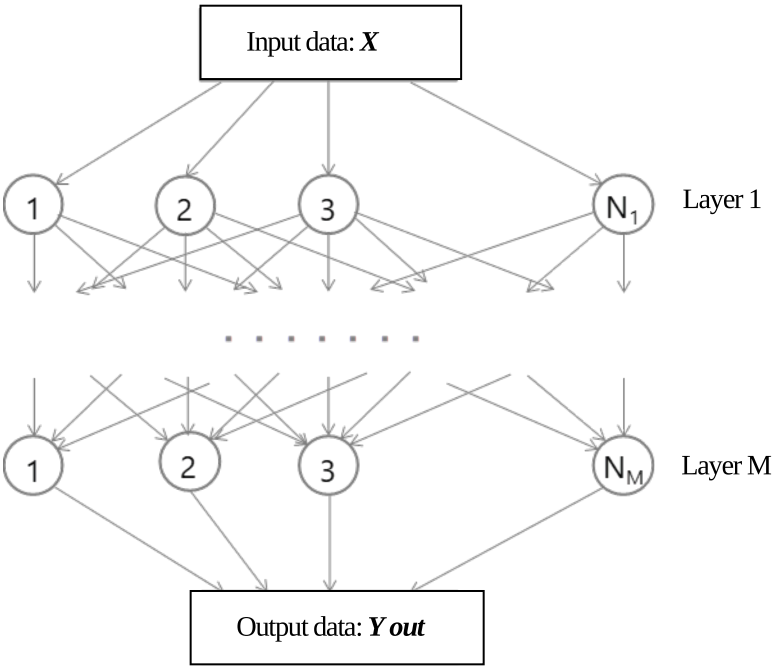
Appendix Table 1-2 Cities whose meteorological data was used

Area	City
Hokkaido	Sapporo
Tohoku	Sendai
Tokyo	Tokyo
Chubu	Nagoya
Hokuriku	Toyama

Area	City
Kansai	Osaka
Chugoku	Hiroshima
Shikoku	Takamatsu
Kyushu	Fukuoka
Okinawa	Naha

Appendix 2 Electricity demand curve estimation model using artificial neural network (ANN)

We used the same ANN-based forecast model that we developed for predicting electricity demand, with some modifications. The ANN is a method for teaching a computer large volumes of data on the non-linear relationship between the input vector and the target value (a scalar or a vector). The concept is illustrated below.



Appendix Figure 2-1 Conceptual diagram of a multi-layer artificial neural network

In this model, M number of middle layers (hidden layers) are set between the input and output layers, and the n-th layer consists of N_n nodes (called neurons). That is, the size (complexity) of the model is determined by the size of M and N_n. If the input data is expressed by a N_0 dimensional vector $\boldsymbol{y_0} = \boldsymbol{X}$, and if the n-th middle layer is expressed by a N_0 dimensional vector $\boldsymbol{y_n}$, output data $\boldsymbol{y_{out}} = \boldsymbol{y_{M+1}}$ can be obtained successively from input data $\boldsymbol{X}$ by postulating the following relative equation:

$$\boldsymbol{y_{n+1}} = \phi(\boldsymbol{w_n}\boldsymbol{y_n} + \boldsymbol{b_n}) \qquad n \in \{0, 1, \ldots, M\} \qquad \text{(Appendix 2.1)}$$

where, φ is a nonlinear function called an activation function, and matrix $\boldsymbol{w_n}$ and vector $\boldsymbol{b_n}$ are parameters called weight and bias, respectively. The nonlinearity of the activation function allows complex events to be modeled and enables highly accurate forecasts.

For teaching the neural network, large quantities of pairs of input data $\boldsymbol{X}$ and output data (teacher data) $\boldsymbol{Y}$ are prepared as learning data. The input data is fed into the network, and $\boldsymbol{w_n}$ and $\boldsymbol{b_n}$ are optimized to minimize the difference between the output data obtained and the teacher data (in many cases, the square of the Euclidean distance between $\boldsymbol{y_{out}}$ and $\boldsymbol{Y}$ is used). Here, this optimization problem is typically solved by using the method for gradient descent. First, the initial values for $\boldsymbol{w_n}$ and $\boldsymbol{b_n}$ are determined, and the descent down the gradient begins from there to an optimal $\boldsymbol{w_n}$ and $\boldsymbol{b_n}$. Thus, the result may differ to a certain extent depending on how the initial values are set. In the model we used, φ is a softplus function $\varphi(x) = \log(1 + e^x)$, the number of layers M is set to 3, and the number of neurons on each layer N_i is 30. Further, Adam was used as the method for gradient descent.

Here, the calendar data (year, month, day, day of week, and whether the day is a holiday) and meteorological data (air temperature, rainfall, and 24-hour solar radiation) for a certain day (day *d*) was used as ***X***, and the 24-hour electricity demand of day *d* as ***Y***. For calendar data, natural numbers were used for the year, month, and day, and for day of week, Sunday was expressed as 0, Monday as 1 … and Saturday as 7. For holidays, 1 is set if the day is a national holiday or falls between December 29–January 3 or August 13–16, and 0 if it does not. Further, all values of the calendar data, meteorological data, and electricity demand data were standardized using the following equation to be used as input and output data for the model:

$$x_t = \frac{X_t - \bar{X}}{X_{max} - X_{min}} \qquad \text{(Appendix 2.2)}$$

where, X_t is the original value, $\bar{X}$, X_{max}, and X_{min} the average, maximum value, and minimum value of X_t, respectively, and x_t the value of input and output data for the model.

Note that the model used in this report used selective ensemble averaging (20 tries). For details on this method, refer to the cited sources.

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