20th International Conference on Renewable Energies and Power Quality (ICREPQ'22)
Vigo (Spain), 27th to 29th July 2022
Renewable Energy and Power Quality Journal (RE&PQJ)
ISSN 2172-038 X, Volume No.20, September 2022

Effect of Demand Forecast Error on Imbalance Cost in Residential Micro Grid

Kohei Nozaki[1], Teruhisa Kumano[2]

[1] Department of Electrical Engineering,
Meiji University
1-1-1, Higashi-mita, Tama-ku, Kawasaki, Kanagawa, 214-8571 (Japan)
e-mail: ce211050@meiji.ac.jp
[2] Department of Electronics and Bioinformatics, Meiji University (Japan)
Phone/Fax number: +81 44 934 7294, e-mail: kumano@meiji.ac.jp

Abstract. In this paper, we conduct electric power simulation by forecasting electricity demand in general households with PV power generation based on the current electricity supply and demand system in Japan. Specifically, forecast errors for electricity demand in general households are taken into account, and machine learning is used to forecast the output of residential photovoltaic power generation. The actual electricity demand, which is the difference between the electricity demand in general households and the PV output, is then calculated, and the degree of contribution of the assumed model to the electricity system is evaluated using an index called imbalance cost from the perspective of a retail electricity provider.

Key words. residential micro grid, error function, neural network, retail electricity provider, imbalance cost

1. Introduction

In recent years, the penetration of renewable energy has been promoted from the perspective of preventing global warming, and the massive introduction of photovoltaic power generation systems, mainly in residential areas, is expected in the future. There are many research papers that forecast the output of renewable energy sources, such as wind and solar power, a few minutes or hours later [1]-[3]. In these papers, prediction methods using neural network, which are part of AI, are proposed. In particular, for PV forecasting, they combine features that include not only past PV output but also other weather data to improve forecast accuracy. However, they vary in the time covered by the forecast and fail to take into account the bidding time of the electricity market. There are currently four electricity markets in Japan: the wholesale electricity trading market, called JEPX which handles kWh; the capacity market, which handles kW; the supply-demand adjustment market, which handles ΔkW , a short-term supply-demand adjustment; and the non-fossil value trading market, which adds environmental value to non-fossil power sources. Of these, Of these markets, the wholesale electricity trading market is particularly active in the trading of electricity for 30 minutes. Since the value of electricity varies during various time periods in this market, it will become increasingly important for generators and retail electricity providers who bid and win bids to make forecasts for which time periods and for how many hours later.

In addition, the deregulation of electric power in Japan started in 2016, changing the restrictions between power generators and retail electricity providers. As a result, when deviating from the balancing rule, an imbalance cost is paid to the transmission and distribution companies based on the amount of electricity that is the difference between the planned and actual values for 30 minutes, which are submitted in advance by the retail electricity providers. However, there are few research papers that quantitatively evaluate the forecast error caused by demand forecasting using imbalance cost [4]. It is necessary to examine the impact of forecasting errors on retail electricity providers.

Therefore, in this paper, we refer to a distribution system in which energy storage devices are installed in a massively installed solar power generation system in a residential area as a residential micro grid (RMG). The authors examine the contribution of RMG to the reduction of imbalance cost by controlling the grid connection point power flow between RMG and the distribution system when a large amount of PV power is installed in 300 households. In addition, we report that when a retail electricity provider uses machine learning to forecast PV output, the forecast accuracy can be improved by varying the input data according to the time of the forecast target and by selecting data that takes seasonal correlation into account.

2. RMG Model and Assumptions for Each Variable

A. Assumed RMG Model

The assumed RMG system configuration is shown in Fig. 1 [5]. In this paper, electricity simulations are performed using this model, in which a large amount of PV power is installed in 300 households.

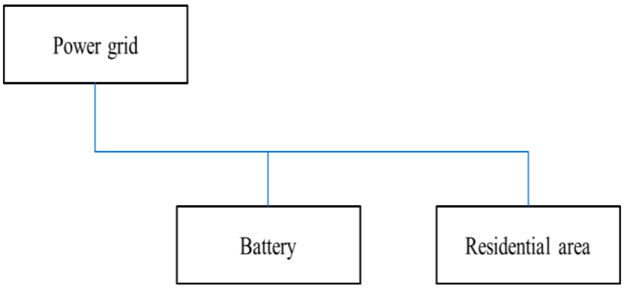

Fig. 1. Residential Micro Grid Model

B. *Assumptions for Each Variable*

The evaluation time period covers the period from 10:00 to 15:00, when the output of solar power generation is large and output fluctuates significantly. Each variable used in RMG is the amount of electricity at the grid connection point power flow $G(t)$ [kW], PV output $P(t)$ [kW], storage battery charge/discharge power $B(t)$ [kW] ($B(t)$ > 0: discharge), and electricity demand $D(t)$ [kW], forming the following relationship equation.

$$G(t) + P(t) + B(t) = D(t)[\text{kW}] \quad (1)$$

1) *Demand for Electric Power: $D(t)$*

The electricity demand $D(t)$ of RMG is formed based on the previously prepared data $D'(t)$ [pu] of electricity demand for 8 households [6]. The electricity demand of RMG is then averaged for 8 households, which is considered to be the electricity demand of one household, and the maximum capacity of each household is set to be 4 [kW], so that the electricity demand of 300 households could be expressed as in the following equation.

$$D(t) = 4 \times D'(t) \times 300[\text{kW}] \quad (2)$$

2) *Total Photovoltaic Output: $P(t)$*

The total output $P(t)$ of RMG's photovoltaic power generation is assumed using one-minute interval solar radiation data from Nara Meteorological Observatory observed in Nara City, Nara Prefecture, Japan on May 1, 2020, with a tilt angle of 30°, and expressed by the following equation.

$$P(t) = (\frac{I(t)}{I_{ref}} \times P_{cap} \times \eta) \times 300 \times R_{pv}[\text{kW}] \quad (3)$$

Note that $I(t)$: solar radiation on sloping surface[kW/m^2], I_{ref}: reference solar radiation(= 1.0[kW/m^2], P_{cap}: rated capacity of PV power generation per household (= 3.8kWp), η: overall efficiency considering inverter and MPPT (Maximum Power Point Tracking) mismatch, etc (= 80%), R_{pv}: PV installation rate among 300 households (= 50%).

3) *Amount of Stored Electricity in Battery Storage $C(t)$*

The amount of stored electricity $C(t)$ in the battery storage is assumed by the following equation, where the maximum capacity is 5 [kWh].

$$C(t) = C(t-1) - B(t)/60[\text{kWh}] \quad (4)$$

C. *Demand and PV Forecasts*

Under the current Japanese electricity supply-demand system, electricity trading is conducted based on the total amount of electricity for 30 minutes. Therefore, in order to forecast actual electricity demand in the assumed RMG, it is necessary to forecast 30 minutes of electricity demand in residential areas and 30 minutes of PV output at the same time. However, due to security reasons, the actual data on electricity demand in residential areas is not available to the public, so the number of data is small and high forecasting accuracy cannot be expected. Therefore, in this paper, the forecasted value of electricity demand, $D_{pred}(t)$, is assumed to be predictable by adding up the error $x(t)$ within ±10% of electricity demand, $D_{pred}(t)$, using the following equation.

$$D_{pred}(t) = D(t)/60 + x(t)[\text{kWh}] \quad (5)$$

Note that t: elapsed time within the evaluation time period [minutes], and $x(t)$: forecast error for 30 minutes.

On the other hand, for the PV forecast $P_{pred}(t)$, machine learning is used to make the forecast. The following describes how the error function $x(t)$ and $P_{pred}(t)$ are created.

1) *How to Create the Error Function $x(t)$*

First, 300 uniform random numbers are created within ±10% of electricity demand, and their cumulative distribution function is shown in Fig. 2. Then, 300 random numbers between 0 and 1 are created, and the horizontal axis $D(t)$ corresponding to the probability on the vertical axis of the cumulative distribution function in Fig. 2 is created as a normal random number.

Next, numerical integration is performed from the following stochastic differential equation (Langevin equation) using the normal random numbers as white noise [7],[8]. This sequence is then repeated 3000 times, and the ensemble average is used as the error function. The backward Euler method, trapezoidal method (Crank Nicolson method), and Runge-Kutta method are used as the integration methods.

$$m\frac{dx}{dt} = -ax(t) + w(t) \quad (6)$$

Note that t: time, x: prediction error, m: inertia term (= 0.04), a: drift term (= 0.5), $w(t)$: white noise (irregular error).

Each error function is created from data for 10 time periods divided into 30-minute intervals from 10:00 to 15:00, the evaluation time period. This error function is shown in Fig. 3.

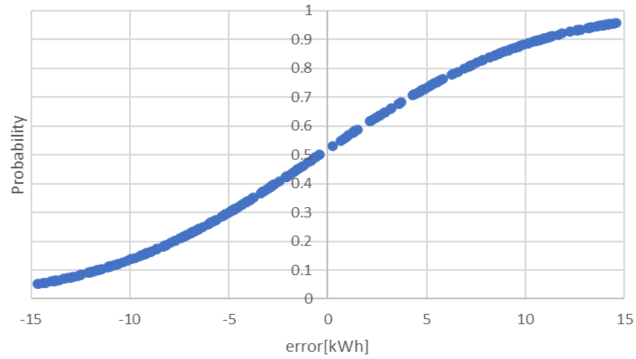

Fig. 2. Cumulative Distribution Function (10:00~10:30)

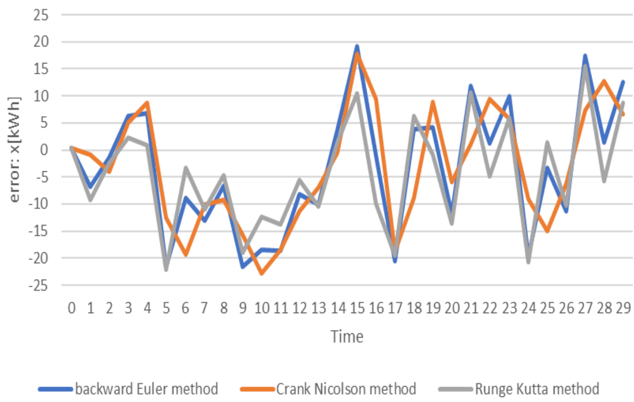

Fig. 3. Error Function (10:00~10:30)

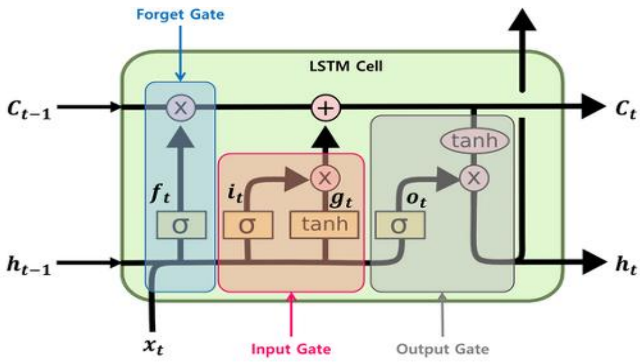

Fig. 4. Each Block in LSTM

2) *PV Forecasting Method: $P_{pred}(t)$*

The PV forecasting method use neural network, a form of machine learning. Among them, RNN (Recurrent Neural Network) has the advantage of treating data as a time series, and has been confirmed to be a very useful method for weather forecasting. Therefore, in this paper, solar radiation forecasting is performed using a conventional RNN and LSTM (Long-Short Term Memory) [9], which enables long-term memory, and the predicted PV output is calculated from equation (3). LSTM is a method developed to deal with the gradient loss and gradient explosion problems that occur when training with conventional RNN, and consists mainly of an input gate, an forget gate, and an output gate, as shown in Fig. 4. The three gates control the flow of information into and out of the cell. Each parameter in Fig. 4 can be expressed by the following equation.

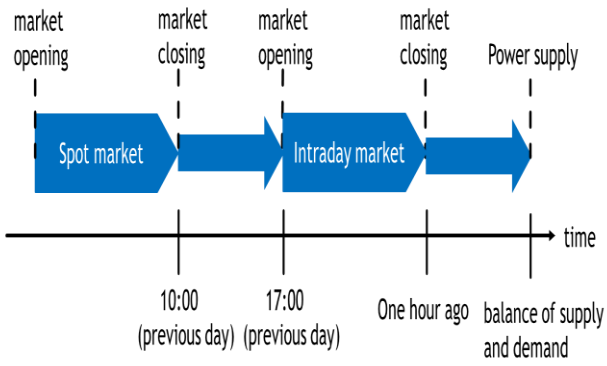

Fig. 5. Spot Market and Intraday Market

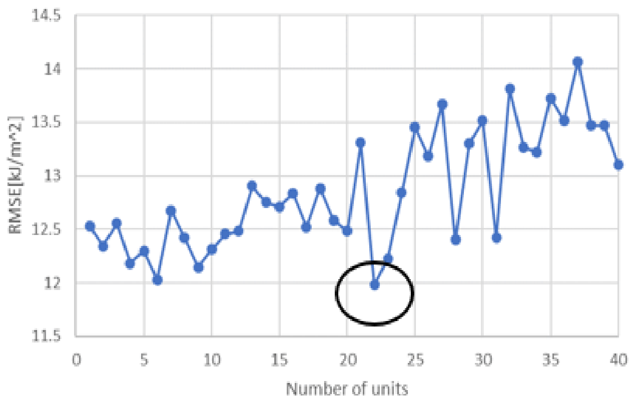

Fig. 6. RMSE for Each Number of Units

Table 1. Learning Parameters for Each of the Neural Network

Number of input layer units	7
Number of middle layer units	22
Number of output layer units	1
Loss function	MSE
Optimization algorithm	ADAM
Learning rate	0.001
Time step	180
Batch size	1024
Output layer activation function	linear

Forget gate: $$f_t = \sigma(W_f \times [h_{t-1}, x_t] + b_f) \quad (7)$$

Input gate: $$i_t = \sigma(W_i \times [h_{t-1}, x_t] + b_i) \quad (8)$$

$$g_t = \sigma(W_c \times [h_{t-1}, x_t] + b_c) \quad (9)$$

Output gate: $$o_t = \sigma(W_o \times [h_{t-1}, x_t] + b_o) \quad (10)$$

$$h_t = o_t \times \tanh(C_t) \quad (11)$$

Cell stage: $$C_t = f_t \times C_{t-1} + i_t \times g_t \quad (12)$$

Currently, the supply and demand of electricity in Japan is traded on JEPX (Japan Electric Power Exchange) for 48 frames of electricity divided into 30-minute units over a 24-hour period. This JEPX has two main markets, called the spot market and the intraday market, as shown in Fig. 5. The spot market is open from 8:00 to 17:00 and trades are conducted for the next day. On the other hand, the intraday market is open 24 hours a day from 17:00 on the previous day and trades are conducted until one hour before the electricity delivery time.

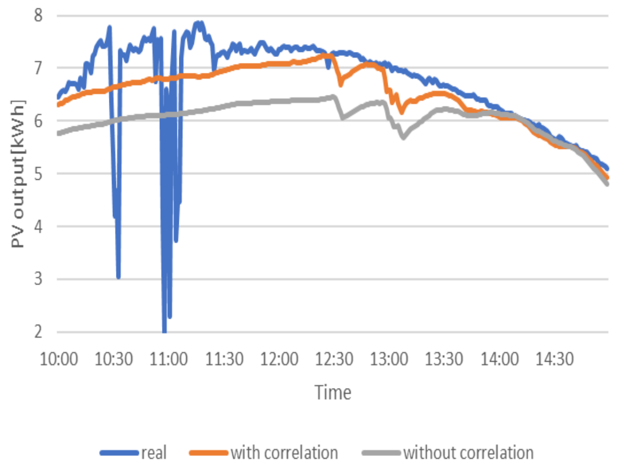

Fig. 7. Comparison of PV Forecast Correlations

Table 2. RMSE by Correlations

	With correlation	Without correlation
RMSE [kWh]	0.6936	0.9997

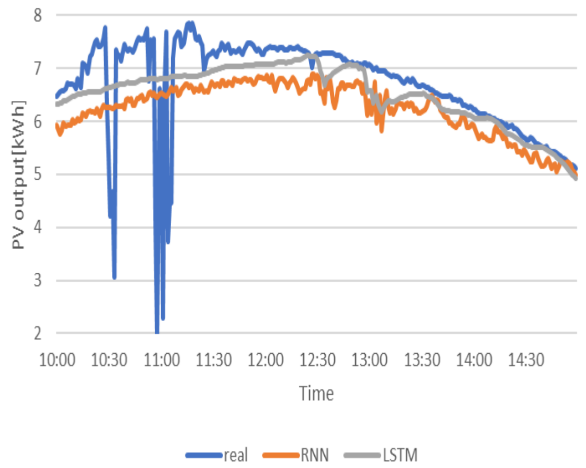

Fig. 8. Comparison of PV Forecasting Methods

Table 3. RMSE for Each Forecasting Method (With correlation)

	RNN	LSTM
RMSE [kWh]	0.8259	0.6936

when retail electricity providers bid in the intraday market, they must decide on the amount to bid at least one and a half hours before the delivery time of electricity. For this reason, this paper assumes the trading hours of retail electricity providers in the intraday market and uses PV output two hours later as the forecast target, taking into account calculation time. The seven characteristic quantities are time, solar radiation, temperature, atmospheric pressure, humidity, wind speed, and weather. When using these features as input data, time steps are simulated for the past 1 hour, 2 hours, and 3 hours, respectively. As a result, the accuracy is best for the past 3 hours, and therefore, the 3-hour time step is used. The input data is then used for the years 2018-2020 observed at Nara Meteorological Observatory. In this case, since it has been confirmed that solar radiation has seasonal correlation, input data should be chosen carefully to improve the accuracy of the forecast [10]. Therefore, in this paper, we check the results of two types of forecasts, one that takes seasonal correlation into account and the other that does not take seasonal correlation into account. Then, we compare the forecasting methods using RNN and LSTM from the data of the one with better forecasting accuracy. In the forecasting that takes seasonal correlation into account, input data for the three months before and after the forecast target is used, and the neural network is used to learn and strengthen the correlation. On the other hand, for forecasts that do not take seasonal correlation into account, data going back 8 months from the forecast target are used as input data. For example, a forecast that takes into account seasonal correlations would learn two months from March to April 2020 and three months each from April to June 2018 and April to June 2019. On the other hand, for forecasts that do not take seasonal correlations into account, eight months are learned from September 2019 to April 2020. In addition, the number of units that resulted in the smallest forecast error when the number of units in the middle layer is increased to some extent is used [11]. Fig. 6 shows this result. In addition, MSE (Mean Squared Error) is used as the loss function and the optimization algorithm is ADAM (Adaptive Moment Estimation). The equation for updating the weight by ADAM is shown below.

$$
\begin{aligned}
m_0 &= v_0 = 0 \\
m_t &= \beta_1 m_{t-1} + (1-\beta_1)\frac{\partial E}{\partial w} \\
v_t &= \beta_2 v_{t-1} + (1-\beta_2)\left(\frac{\partial E}{\partial w}\right)^2 \\
\widehat{m_\tau} &= \frac{m_\tau}{1-\beta_2^\tau} \\
\widehat{v_\tau} &= \frac{v_\tau}{1-\beta_2^\tau} \\
w &= w - \alpha\frac{\widehat{m_\tau}}{\sqrt{\widehat{v_\tau}}+\varepsilon}
\end{aligned}
\tag{13}
$$

Note that $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\alpha = 0.001$, $\varepsilon = 10^{-8}$, m: first moment estimate, v: second raw moment estmate τ: number of parameter updates, w: weight.
Each parameter in this ADAM uses the recommended parameters [12].

Using these numbers of units, a three-layer neural network is constructed and forecasts are made. The values of these learning parameters are shown in Table 1.
Fig. 7 shows the results of PV forecasts with and without seasonal correlation at May 1, 2020, and the RMSE (Root Mean Squared Error) is shown in Table 2. From this, it can be confirmed that the PV output forecast accuracy improves when the seasonal correlation is taken into account. Table 3 shows the RMSE for the forecast results of RNN and LSTM for the forecast with seasonal correlation. Fig. 8 confirms that LSTM is more accurate than RNN, but it is not able to follow the rapid PV fluctuation from 10:00 to 11:30, respectively. The cause of this is thought to be influenced by the parameters of the neural network, such as activation function, number of training cycles, and batch size, but the main reason is that training data close to the actual values were not prepared.

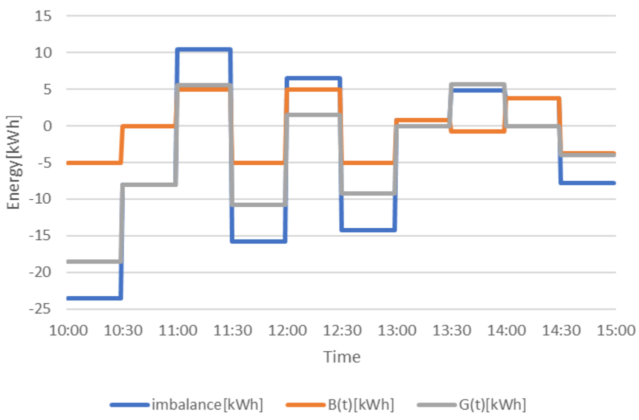

Fig. 9. Each amount of Power

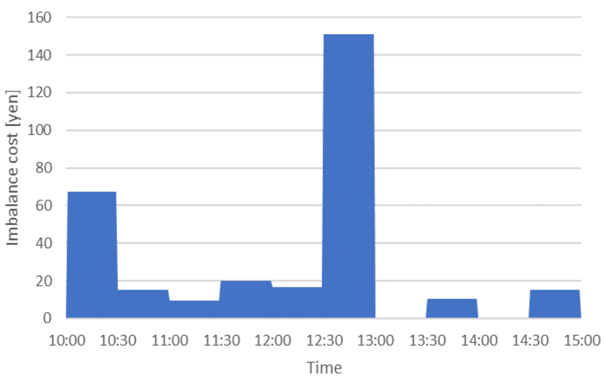

Fig. 10. Imbalance Cost during the Evaluation Time Period (LSTM)

Table 4. Comparison of Imbalance Cost

	RNN	LSTM
Surplus imbalance cost[yen]	713.04	268.69
Insufficient imbalance cost[yen]	0	36.75
Total imbalance cost[yen]	713.04	231.94

Therefore, it is possible that better forecasting results can be obtained by including past data in which sudden fluctuations occurred as training data. In addition, since it is necessary to optimize the parameters, improvement of the training data and the forecasting method is an issue to be addressed in the future.

3. Simulation Result

Fig. 9 shows the relationship among the grid connection point power flow $G(t)$, battery recharge/discharge power $B(t)$, and imbalance power flow during the evaluation time period using the Crank Nicolson method and LSTM.
Fig. 9 shows that at the retail electricity providers, the insufficient imbalance is not completely resolved at 11:00 to 11:30, 12:00 to 12:30, and 13:30 to 14:00, and the surplus imbalance is not completely resolved at 10:00 to 11:00, 11:30 to 12:00, 12:30 to 13:00, and 14:30 to 15:00 even when the battery storage is charged and discharged. Based on these results, the imbalance costs for each time period according to the unit cost of imbalance costs on May 1, 2020 are shown in Fig. 10, and a comparison of costs in RNN and LSTM is shown in Table 4 [13]. At present, there is no clear standard to indicate the degree of contribution to maintaining the supply-demand balance of the grid, since there is no obligation to implement the same amount as the planned value in the microgrid. Therefore, we assume the imbalance cost paid by conventional retail electricity providers as a penalty for RMG. The result is that RMG receives 713.04 yen when forecasted by RNN and 231.94 yen when forecasted by LSTM. Fig. 10 shows that the imbalance costs are significantly larger from 10:00 to 10:30 and from 12:30 to 13:00 during the evaluation time period. We consider that these time periods are due to the creation of stochastic errors and particularly inaccurate PV power generation forecasts. To reduce imbalance costs during these time periods, we consider that, as mentioned earlier, there is a need to be devised in training data and forecasting methods, and to plan bids more strategically based on market bidding time.

4. Conclusion

This paper limits the bidding time of retail electricity providers to a few hours before the electricity market closes, but shows how RMG reduced imbalance costs by recharging and discharging storage batteries, while at the same time reducing imbalance power by the same amount. Electric power simulation using an error function and neural network confirm the need to consider seasonal correlation in PV output forecasting and that LSTM has higher forecasting accuracy than RNN. In that case, the prediction was made from the standpoint of a retail electricity provider by considering the bidding time and seasonal correlation in the electricity market, but it is necessary to further improve the prediction accuracy by successively changing each parameter of the neural network and the input data. Although a three-layer neural network is used in this paper, it may be possible to further improve the forecasting accuracy by increasing the number of middle layers and using deep learning.

Therefore, in the future, the authors are going to apply the deep learning and to consider various input data patterns and make predictions. The authors also intend to consider bidding times from several days in advance to reduce imbalance costs, which are important for retail electricity providers.

Acknowledgement

This work was supported by JSPS KAKENHI Grant Number 16K06242.

References

[1] Atsushi Yona, Tomonobu Senju, Toshihisa Funabashi, Hideomi Sekine, "Application of Neural Network to 24-hours-Ahead Generating Power Forecasting for PV System", IEEJ Trans. PE, Vol.128, No.1, pp. 33-40 (2008)
[2] Atsushi Yona, Tomonobu Senju, Naomitsu Urasaki, Toshihisa Funabashi, "Application of Recurrent Neural Network to 3-Hours-Ahead Generating Power Forecasting for Wind Power Generators" IEEJ Trans. PE, Vol.129, No.5, pp. 591-597 (2009)
[3] Yutaka Sasaki, Naoto Yorino, Farid Imam Wahyudi, Dai Seikoba, Mitsumasa Asaba, Liying Ma, Yoshifumi Zoka, "A Simple and Reliable PV Forecasting Method for Local Area

Energy Management", IEEJ Trans. PE, Vol.137, No.7, pp. 538-545 (2017)
[4] Chika Wada, Satoshi Takayama, Yoshihiko Susuki, Atsushi Ishigame, Kazuhiro Deguchi, Kouta Konishi, Daisuke Ishizuka, Kenichi Tanaka, "A Multi-Scale Supply Operation of Grid-connected Micro-Grid", IEEJ Trans. PE, Vol.140, No.3, pp.166-175(2020)
[5] Takeyoshi Kato, Hiroshi Yamasaki, Yasuo Suzuki, "A Study on Dumping Power Flow Fluctuation at Grid-Connection Point of Residential Micro-Grid with Clustered Photovoltaic Power Generation Systems Considering Difference in Solar Irradiance Patterns in Urban Districts", IEEJ Trans. PE, Vol.130, No.3, pp. 305-312 (2010)
[6] Satoshi Nomoto, Teruhisa Kumano, "Optimal Operation Planning for Residential PEFC Cogeneration System Considering Periodical Boundary Constraints Concerning Hot Water in Storage Tank", IEEJ Trans. PE, Vol.136, No.6, pp. 547-556 (2015)
[7] Myung-man Kim, Andrew L. Zydney, "Effect of electrostatic, hydrodynamic, and Brownian forces on particle trajectories and sieving in normal flow filtration", Journal of Colloid and Interface Science, Vol.269, pp.425-431(2004)
[8] Ryosuke Nakagawara, Satoshi Uchida, Taiichi Shibuya, Hiroyuki Nishikawa, "Numerical Simulation of Gold Nanoparticles Dynamics in Dielectrophoretic Assembly", IEEJ Trans. SM, Vol.137, No.4, pp. 107-114(2017)
[9] Sepp Hochreiter, Jürgen Schmidhuber, "Long Short-Term Memory", Neural Computation 9, pp. 1735-1780(1997)
[10] Shoji Kawasaki, Hisao Taoka, Taiki Nagao, Keisuke Onaka, "Development of Insolation Forecasting Method by Genetic Algorithm", IEEJ Trans. PE, Vol.135, No.2, pp. 89-96 (2015)
[11] B. Kermanshahi, "Recurrent neural network for forecasting next 10 years loads of nine Japanese utilities", Neurocomputing, Vol.23, No.1-3, pp. 125-133(1998)
[12] Diederik P. Kingma, Jimmy Lei Ba, "ADAM: A METHOD FOR STOCHASTIC OPTIMIZATION", ICLR(2015)
[13] Kansai Transmission and Distribution: "about the imbalance cost unit price", https://www.kansai-td.co.jp/consignment/agreement/imbalance.html (Accessed on March 15, 2022)