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Same-day correction of baselines for demand response using long short-term memory

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Abstract. In incentive-based the Demand Response, the amount of electricity demand reduction is calculated by subtracting actual electricity demand from the baseline (BL). The BL is the estimated electricity demand of households when no electricity demand suppression is performed. In Japan, the high 4 of 5 method is used to forecast the BL by averaging the actual demand of the day. In this study, we refer to the high 4 of 5 method as BL1. BL2 is the BL to which the value of the same-day adjustment is added based on the actual demand of the day. BL3 is BL1 plus the value of the same-day adjustment predicted using Long Short-Term Memory (LSTM). The average MAE values for BL2 and BL3, calculated using actual electricity demand data from October 15, 2021, to December 24, 2021, were 11.2 kW and 8.1 kW, respectively, with BL3 being 3.1 kW smaller than BL2. To estimate the confidence intervals for BL2 and BL3, we calculated the error by subtracting each BL from the actual value and calculated the $\pm 3\sigma$ equivalent for the distribution of the error. The confidence interval calculated for BL3 was found to be ±9.2 kW lower than that for BL2. The F-test for the distribution of the errors for BL2 and BL3 yielded a P-value of 4.05 × 10-50, indicating that the variances of the two distributions were not equally distributed.

1 Introduction

In recent years, with the increase of remotely controlled facilities on the demand side, such as storage batteries, electric vehicles, and heat pumps, the Demand Response (DR) has been attracting attention as a function to ensure the balance between supply and demand of electricity. According to Han J and Piette M A, DR is defined as a short-term change in electricity consumption patterns to reduce or shift electricity loads [1]. DR can be broadly classified into two types: fee-based DR and incentive-based DR. In incentive-based DR, compensation is paid to consumers based on the amount of electricity demand reduction, which is calculated by subtracting actual electricity demand from the baseline (BL). The BL is the estimated electricity demand of households when no electricity demand suppression is performed. In contrast, electricity demand includes load facilities other than

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those used for DR. When performing DR, it is necessary to forecast BL and control demand facilities, but the amount of demand suppression is affected by fluctuations in electricity demand outside the control target [2]. In order to actively utilize DR, it is necessary to forecast BLs with high accuracy, taking demand fluctuations into account. In addition, since BL contributes to the incentives allocated to consumers and influences the securing of consumer resources, highly accurate forecasting and setting are required [3]. Electricity demand fluctuates with time, therefore, it is often associated with short-term electricity demand forecasting. In the past, methods using time series analysis such as linear regression, autoregressive and autoregressive moving average models, recurrent neural networks, Long Short-Term Memory, and other artificial neural networks have been proposed for short-term electricity demand forecasting [4, 5, 6, 7]. In Japan, methods such as correcting the value of electricity demand immediately before the high 4 of 5 have also been proposed [8]. There are studies that have examined electricity demand forecasting; however, few have focused on correction methods. The objective of this study was to reduce the variance of the forecast error between BL and electricity demand by using the forecast error between BL and actual values for the training data of LSTM and applying the last-minute correction value predicted using LSTM to the last-minute correction value of BL. For this purpose, two types of BL were prepared, normal BL and BL utilizing LSTM, and the forecast errors were compared with the actual values of electricity demand.

2 Method

2.1 Electricity demand data

A research facility of Kyoto University with a maximum power of 511 kW was targeted, and the pulse values transmitted from the smart meter according to the amount of electricity were converted to power values. The data (one-minute values) acquisition period was from 14 December 2020 at 0:00 to 24 December 2021 at 23:59. During the data acquisition period, unusually high-power values, such as 0 kW and >10,000 kW, were observed between 1:06 and 1:11. These values were linearly interpolated from the 1:05 and 1:12 minutes values. In addition, the missing data during the data acquisition period were linearly interpolated by the values before and after the missing values. In this study, we evaluated the value at 30 minutes. In addition, we used data up to one hour before the period covered by the forecast.

2.2 BL evaluation methods

Referring to previous studies [3, 9, 10], mean absolute error (MAE) and mean error (ME) were calculated to evaluate the accuracy of BL. MAE is the absolute value of the difference between the BL value and the actual demand data calculated for each data point, and the sum of the values divided by the number of data points. The lower the MAE, the higher the accuracy of BL estimation. A BL with a positive ME value tends to overestimate the actual electricity demand of consumers, while a BL with a negative ME value underestimates it.

2.3 BL prediction methods using averaging method

The high 4 of 5 is used for forecasting of BL by the averaging method, based on the actual demand of the day in Japan [8]. In this paper, we refer to the high 4 of 5 as BL1. The value of the same-day adjustment for BL1 is the value obtained by subtracting the average of the high 4 of 5 energy demand during the same period from the average of the energy demand from 5 to 2 hours before the forecast period. The BL to which the value of the same-day adjustment is added based on the actual demand of the day is referred to as BL2. Figure 1 shows the above.

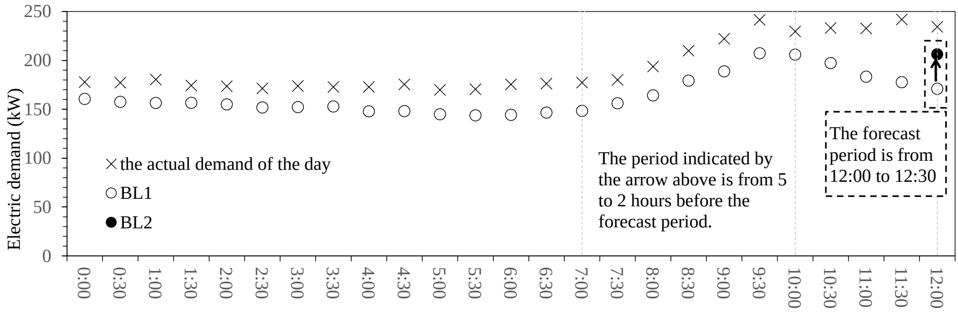

Fig. 1. Example of BL2 with the same-day adjustment for BL1 during the forecasted time period from 12:00 to 12:30.

2.4 Method for prediction of BL same-day correction values using LSTM

In this study, BL3 is BL1 plus the value of the same-day adjustment predicted using LSTM. The 30-minute electricity demand data and the deviation from BL1 data were prepared to predict the value of the same-day adjustment using LSTM; 80% of this data was used as training data and 20% as test data to develop the prediction model for the correction value applied to BL3. The circles described in Figure 2 represent nodes containing values, and a collection of nodes is a layer. For the hidden layer, LSTM, batch normalisation, and all joins were used. A layer is a collection of nodes, batch normalisation is a method to increase learning efficiency by normalizing the nodes in a layer, and all joins is a joining of all nodes in the previous and next layers [11,12]. The number of outputs of the LSTM and batch normalisation layers is 64, and the output of the all-joining layer is one layer.

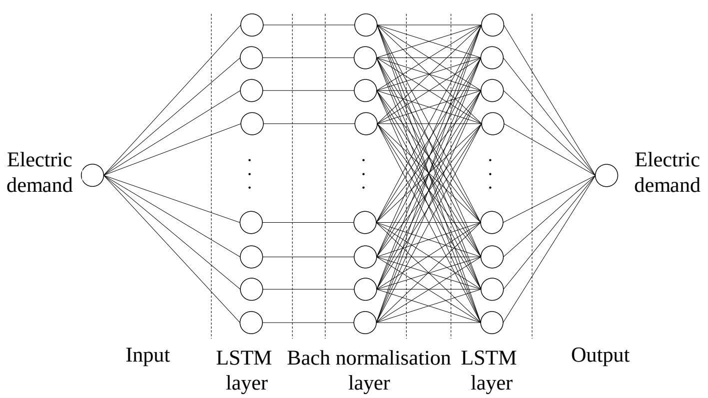

Fig. 2. LSTM model used to predict same-day correction values for BL 3.

The relationship between the length of time used for input data and the accuracy of BL3 forecasts using the one-hour-ahead correction values was examined. One step in the previous time step was 30 minutes, and the length of time used for input data is shown in Table 1. The relationship between the predicted and actual ME and MAE for each length of time used for the input data was determined using the actual power demand data from 15

October 2021 to 24 December 2021, which was the test data. The length of time used for input data in this study was determined to be 8 steps.

Table 1. ME and MAE for each previous time step used for input data.

Previous time step	1	2	4	6	8	10
ME (kW)	4.30	3.56	-0.33	0.83	0.09	-3.37
MAE (kW)	7.46	6.99	6.30	6.36	6.30	6.98

3 Results

3.1 Comparison of MAE for BL2 and BL3

During the test data period, BL2 and BL3 were used to determine the error from actual electricity demand. The MAE for each 30-minute period was averaged over the entire test data period. The calculation time period was chosen to coincide with the use of DR as the adjusting power to compensate for forecast errors in variable power sources, such as photovoltaic power generation [10]. The results of MAE for each BL in 30-minute increments are shown in Figure 3.

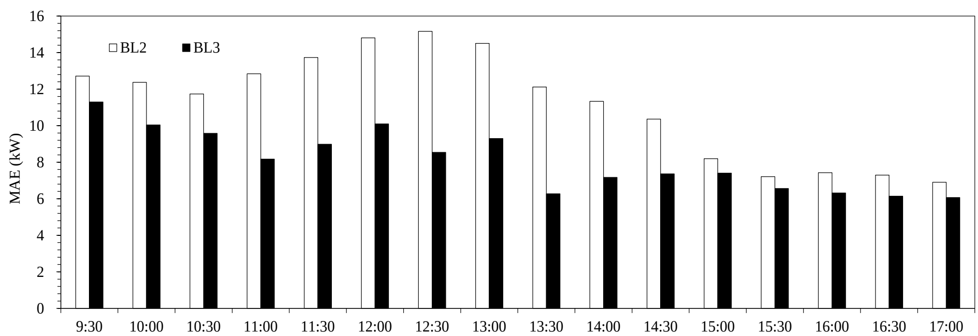

Fig. 3. Comparison of MAE by time period for BL 2 and BL3 during the evaluation period.

The average MAE values for BL2 and BL3 across all calculated periods were 11.2 kW and 8.1 kW, respectively, with BL3 having a value 3.1 kW smaller than BL2. Figure 3 shows that the MAE using BL3 was always smaller than that using BL2 during the period under study, suggesting that learning the difference between BL1 and electricity demand data up to one hour earlier improves the accuracy of the correction value for the same-day adjustment. This is probably because the error values can be characterized as time-series data by maintaining the memory of the data as time-series data.

3.2 Estimation of confidence intervals for BL

Confidence intervals for BLs were estimated by determining errors from actual values for BL2, which is a conventional BL formulation method, and BL3, which is based on the high 4 of 5; the errors were corrected on the same day using LSTM. Estimation was performed by calculating the 3 σ equivalent for the distribution of errors obtained from the actual half-hourly electricity demand values from the evaluation period (15 October 2021 to 24

December 2021) and calculating BL2 and BL3 for the same period. The distribution of errors for the evaluation period and the upper and lower bounds of the 3 σ equivalent confidence intervals are shown in Figure 4 and Figure 5.

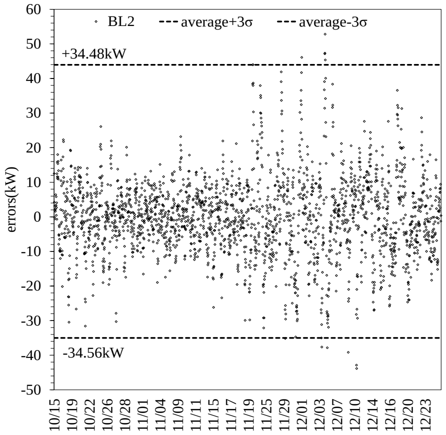

Fig. 4. Distribution of BL2 errors during the evaluation period.

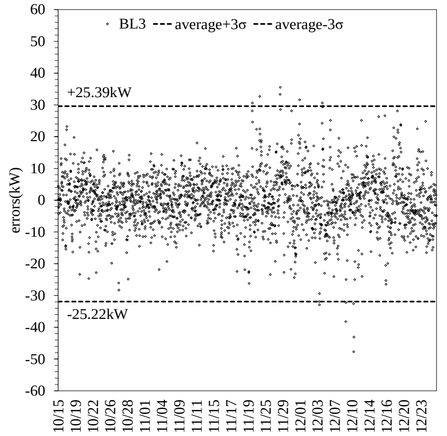

Fig. 5. Distribution of BL3 errors during the evaluation period.

The ME during the evaluation period for BL2 was -0.04 kW with a confidence interval of -0.04 ± 34.52 kW, while the ME for BL3 was 0.08 kW with a confidence interval of 0.08 ± 25.40 kW. Thus, the confidence interval calculated for BL3 compared to that of BL2 was found to be reduced by ±9.2 kW. The F-test for the errors calculated using BL2 and BL3 yielded a P-value of 4.05 × 10^{-50}.

4 Conclusion

We proposed a method of BL3 that uses LSTM to learn from the errors between BL1, a conventional method of creating BLs, and BL2, a conventional correction method for same-day adjustments in BL1 based on actual power demand, and found that BL3 did not differ much from the ME by half-hourly increments during the evaluation period than that of BL2. To estimate the confidence intervals for BL2 and BL3, we calculated the error by subtracting each BL from the actual value, and calculated the ±3 σ equivalent for the distribution of the error. The confidence interval calculated for BL3 was confirmed to be ±9.2 kW lower than that for BL2. The F-test for the distribution of the errors for BL2 and BL3 yielded a P-value of 4.05 × 10-50, confirming that the variances of the two distributions were not equally distributed. This suggests that BL3 method, which combines the averaging method with a same-day correction value applying LSTM to the prediction error, may improve the prediction accuracy of BLs used for DR. The data used in this study is electricity demand data from a single laboratory; therefore, in consideration to DR operations, it is necessary to study a case in which multiple consumers are investigated together. In addition, it is necessary to verify the effects of seasonal fluctuations and other factors on electricity demand by conducting verification throughout the year.

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