A Prediction of Power Demand using Weather Forecasting and Machine Learning: A Case of a Clinic in Japan

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***Abstract*—There is a need to accelerate research and development for an energy saving and a demand response using a renewable energy system because the supply and demand of a power is tight worldwide since 2021. Since hospitals and clinics are heavy power demand, there are promote energy conservation by using distributed energy that actively utilizes renewable energy. Recently, clinics installing a photovoltaic (PV) in combination with a diesel generator (DG) for an energy saving and/or a peek cut of a demand have been more. So, it's necessary for medical staff to predict a power demand, assuming an energy saving and/or a short-term operation. Therefore, this paper proposes the prediction method of a power demand for medical facilities using the weather forecasting data. A neural network (NN) of the prediction method is used the weather forecasting data in the area of medical facilities announced by Japan Meteorological Agency (JMA) are gathered for a long-term as an input. As a result, it is shown that power demand can be predicted with high accuracy.**

Keywords*—*clinic, load prediction, weather forecasting, machine learning

I. INTRODUCTION

There is a need to accelerate research and development for an energy saving and a demand response using a renewable energy system because the supply and demand of a power is tight worldwide since 2021[1]. Since hospitals and clinics are heavy power demand, there are promote energy conservation by using distributed energy that actively utilizes renewable energy. Recently, clinics installing a photovoltaic (PV) in combination with a diesel generator (DG) for an energy saving and/or a peek cut of a demand have been more. So, it's necessary for medical staff to predict a power demand, assuming an energy saving and/or a short-term operation.

As a general method, it has been focused on the correlation between temperature and power demand and find the transmission end power as the regression coefficient of the correlation with the maximum temperature with respect to power demand [2] and examine the effect of the temperature rise in the city on power consumption [3], and so on. In addition, although previous studies such as short-term power demand forecasting [4] using neural networks have been reported. The others on a neural network method for a prediction of power demand is presented a short-term load demand forecasting based on the method of a long-short term memory (LSTM) [5][6]. Also, a novel deep learning approach using data merging for energy consumption data, weather information and time lags etc is proposed [7]. However, a prediction method using weather forecasting as input data it remains to be proposed, yet. Since a weather information is removed after the measured of real weather data, it is difficult to refer as a long-term data.

In this study, a weather forecasting data in the area of medical facilities announced by Japan Meteorological Agency (JMA) are gathered for a long-term. Therefore, this paper presents the prediction method of a power demand for medical facilities using the weather forecasting data. A neural network (NN) of the prediction method is used the weather forecasting data as a input.

II. POWER DEMND OF A CLINIC

A. A clinic grid

Figure 1 shows a utility grid and an emergency power system with coupled a DG and a PV in a conventional clinic grid. There is one DG system connected to a grid of on-site power generation as existing. Since the clinic require to reduce contract power, promoting to use a DG and a PV.

B. Power demand of a clinic

Figure 2 shows the actual total power demand for 24 hours in a clinic in February and June. The vertical axis is power [kWh], and the horizontal axis is time [hour]. The solid blue line represents the load in June, and the solid red line represents the load in February. Both load pattern has similar characteristics, before 6:00 there is an almost constant low load, which increases gradually after 6:00 because of breakfast preparation. After 8:00, the daytime power consumption during the outpatient services time indicates a broad peak.

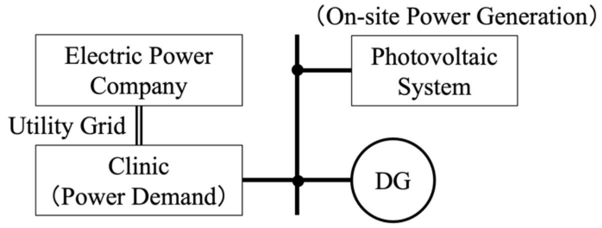

Fig. 1. A clinic grid as a smart grid.

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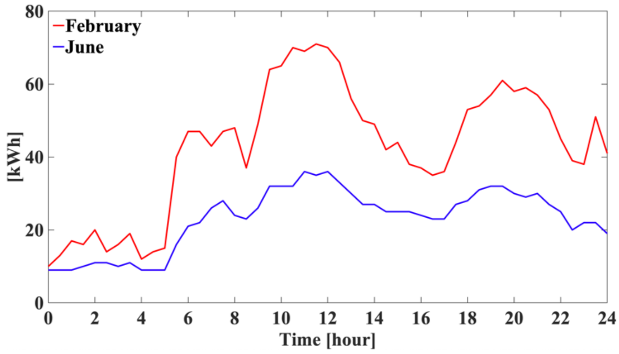

Fig. 2. Hourly load profile of February and June in a clinic.

III. Machine Learning with Neural Network

A. Standardized power demand

The weather distribution forecast and regional time series forecast of the JMA are the weather every 3 hours (5 types of swelling / cloudy / rain / snow / rain or snow), temperature and wind speed in 14 sections from 6:00 on the day to 21:00 on the next day. The wind direction (8 directions) will be announced at 5 o'clock in the early morning and will be updated at 11 o'clock and 17 o'clock on the day. In this paper, the weather forecast announced by the JMA at 5 o'clock on the day is used as a predictor, and the actual contract power is used as a learning target for learning with a neural network. For the actual data of the contracted power of the predictor and the learning target, x'_i standardized using Eq. (1) is used. Here, x_i is the value based on each unit system, and $\bar{x}$ and σ are the mean value and standard deviation. Fig. 3 shows the standardized power demand from January 2021 to March 2022 used by Eq. (1).

$$x'_i = \frac{x_i - \bar{x}}{\sigma} \tag{1}$$

B. A prediction model for a machine learning

Figure 4 shows a prediction model for machine learning. The prediction model is designed with 3 hidden layers and 30 nodes for each layer. Table 1 shows the predictors given to the input layer. The input layer is divided into four, input 1 is the number of contracts, input 2 is the day of the week and the season, input 3 is the weather forecast for the day, and input 4 is the weather forecast for the next day.

For the day of the week, the integer 1 to 7 is converted from Sunday to Saturday, and the holiday is the same as Sunday. For the season, the integer value 1 is set from March to June, and 1 is added every 4 months. The weather forecast uses the temperature forecast from 6:00 on the day to 21:00 on the next day.

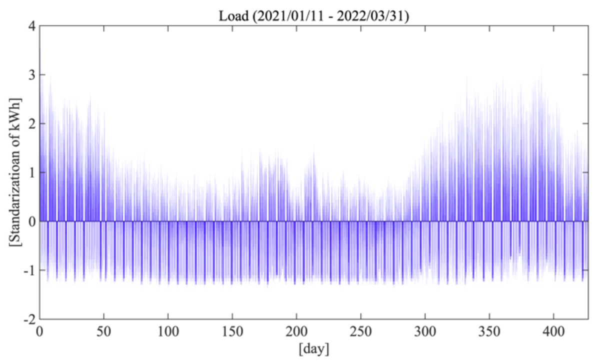

Fig. 3. Standardized power demand of a clinic.

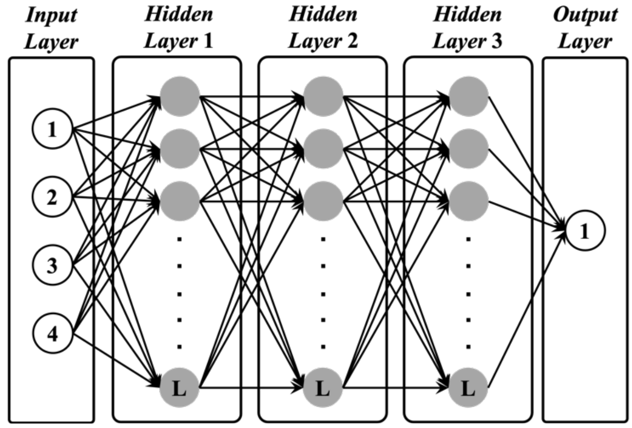

Fig. 4. Configuration of a machine learning by neural network.

TABLE I. Input Layer

1	2	3	4
Power demand From 11th Jan. 2021 to 31th Mar. 2022	Day of the week and season	The day weather forecast every 3 hours	The next day weather forecast every 3 hours

TABLE II. Output Layer

1			
Power demand 1	Power demand 2	...	Power demand 48

The output layer is given electric energy (48 pieces) every 30 minutes on the same day as the next day's weather, and learning is performed by a neural network. All the data in the input layer and the output layer are standardized and trained by the same method as in Eq. (1).

IV. Model Evaluation

Figure 5 shows regression results of load Dataset for training, validation, testing, and all of Dataset. The hidden layer is three with thirty neurons and one output layer in each layer shown in Chapter III.

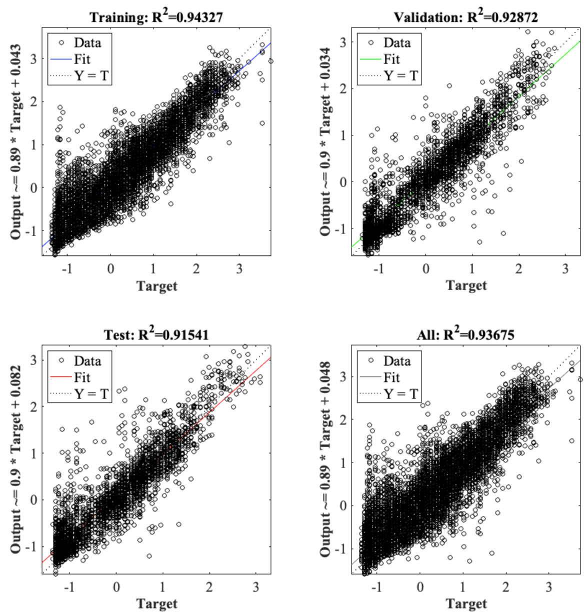

Fig. 5. Difference between regression and performance plot.

In the figure, the horizontal axis indicates the output target and vertical axis denotes the output of prediction results using the NN. The regression results are evaluated by the following Eq. (2) of a coefficient of determination R^2, where $\bar{L}$ is the mean of L. $\hat{L}$ is the predicted clinic load by the NN. The regression analysis can be realized a coefficient of determination R^2 of 0.94327 for training, 0.92872 for validation, 0.94327 for testing and 0.93675 for all Dataset.

$$R^2 = 1 - \frac{\sum_k (L - \hat{L})^2}{\sum_k (L - \bar{L})^2} \tag{2}$$

Figures 6 shows the prediction results using the model in Fig. 4. A graph shows the results of using the measured clinic load in June 2021. In all of the graphs, the vertical axis is the power demand [kWh], and the horizontal axis is time, from 0 to 24 [hour]. The solid blue line represents an actual clinic load, and the solid red line represents the predicted load.

Figures 7 is as in Fig. 6, but for the results that uses the measured clinic load in February 2022.

The prediction errors are shown in Table III. The errors are evaluated by the mean square error (MSE) [kWh^2], the root mean square error (RMSE) [kWh], the mean absolute error (MAE) [kWh], and the ratio of RSME to MAE shown in from Equation (3) to (5). The RSME / MAE ratio [-] results are 1.37 for June 2021 and 1.50 for January 2022, respectively, which are close to the general machine learning evaluation value $\sqrt{\pi/2} \approx 1.253$. The proposed machine learning method is shown that the special features of clinic power demand is captured.

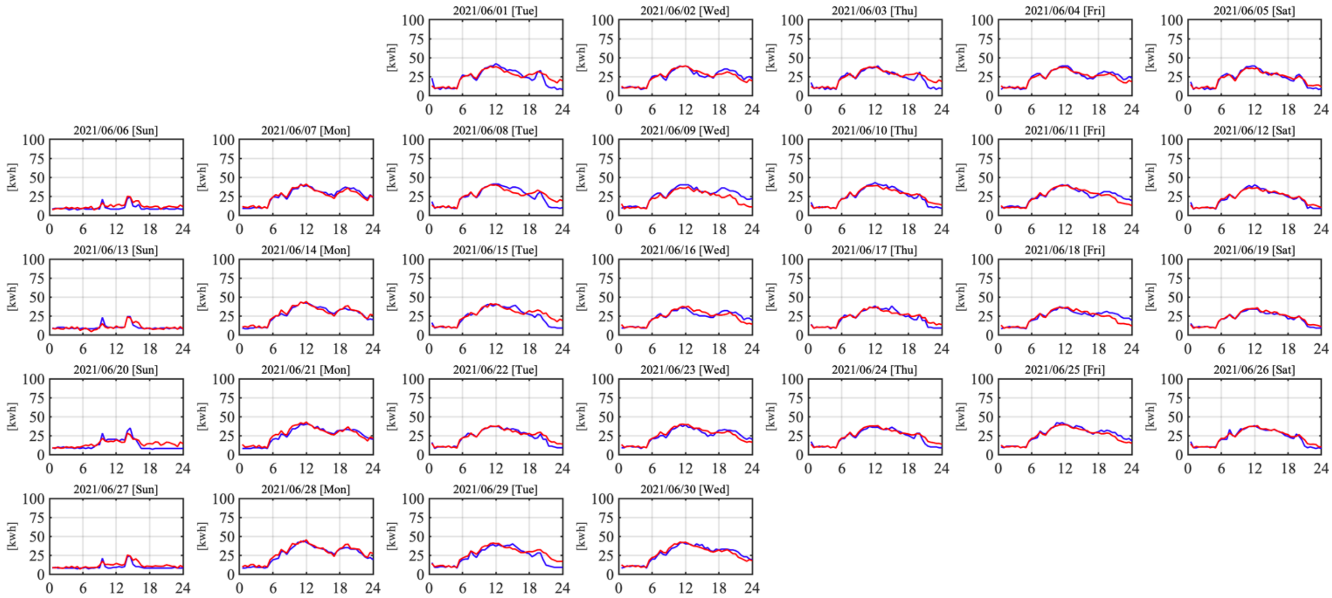

Fig. 6. Comparison of monthly forecast power demand and actual demand in June 2021.

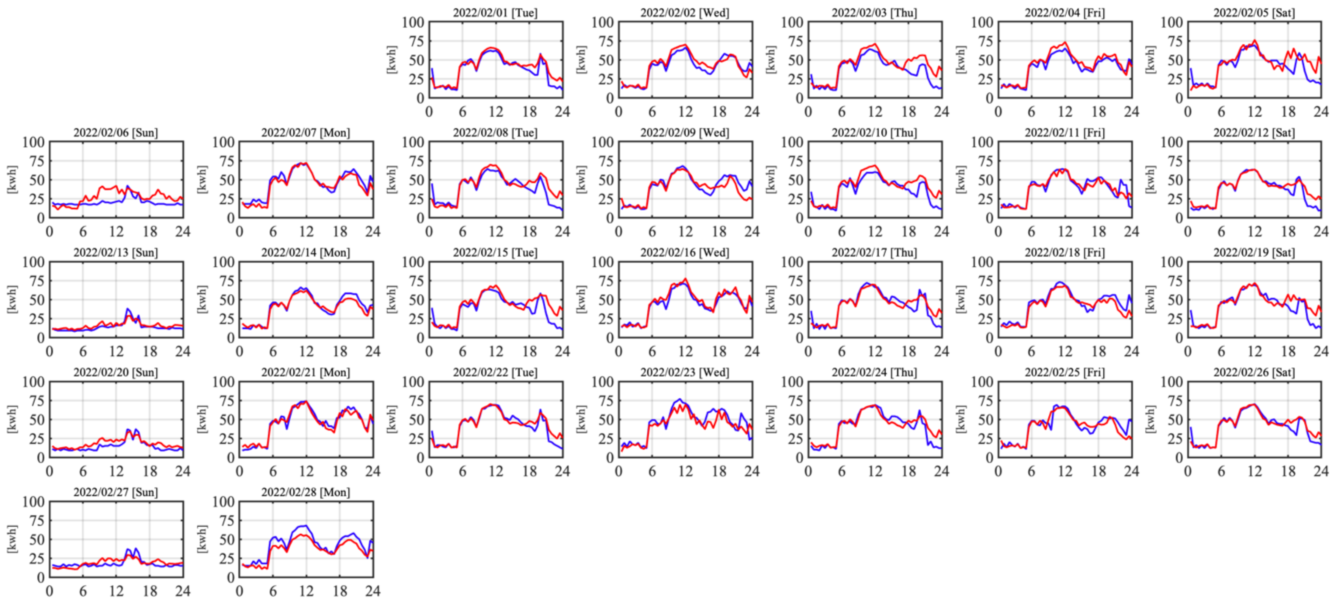

Fig. 7. Comparison of monthly forecast power demand and actual demand in February 2022.

TABLE III. PREDICTION ERRORS

Year	Month	MSE [kWh^2]	RMSE [kWh]	MAE [kWh]	RSME / MAE [-]
2021	1	30.12	5.49	3.75	1.47
	2	47.74	6.91	5.04	1.37
	3	39.69	6.30	4.57	1.38
	4	24.72	4.97	3.47	1.43
	5	19.81	4.45	3.19	1.39
	6	13.72	3.71	2.70	1.37
	7	12.38	3.52	2.53	1.39
	8	17.93	4.23	3.25	1.30
	9	28.94	5.38	3.87	1.39
	10	15.09	3.88	2.87	1.35
	11	12.51	3.54	2.66	1.33
	12	19.09	4.37	3.12	1.40
2022	1	42.94	6.55	4.36	1.50
	2	79.66	8.93	6.05	1.48
	3	56.95	7.55	5.38	1.40
	4	25.40	5.04	3.53	1.43

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{L} - L)^2 \tag{3}$$

$$RMSE = \sqrt{MSE} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{L} - L\right| \tag{5}$$

V. CONCLUSIONS AND OUTLOOK

This paper proposes the prediction method of a power demand for medical facilities using the weather forecasting data. A NN of the prediction method is used the weather forecasting data in the area of medical facilities announced by JMA are gathered for a long-term as an input.

The results are summarized as follows:

(1) A load prediction method that us es a machine learning with actual clinical data and weather information data recorded by the JMA is proposed using MATLAB.

(2) The machine learning used the weather information data and actual clinic load as the one-step-previous load, and the RSME/MAE ratio shows 1.37 in June 2021, and It denotes 1.50 in February 2022.

The proposed power demand forecasting model will be extended and verified to a system that can be put into practical use in future work.

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