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WIND POWER GENERATION PREDICTION BASED ON WEATHER FORECAST DATA USING DEEP NEURAL NETWORKS

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Abstract. *Wind power generation is one of the most important renewable energy sources. Although predicting the amount of power generation is crucial for efficient operations, it is not easy because of fluctuating nature of wind speed. This paper applies a deep neural network method to predicting wind power generation based on weather forecast data. Wind power generation data were collected from a power plant located in Jeju, South Korea, and weather forecast data for the nearby weather stations were collected. The prediction performance of the model was evaluated with wind power generation data and weather forecast in terms of root mean square error, mean square error, mean absolute error, and R-squared.*
Keywords: Renewable energy, Weather forecast data, Wind power generation data, Deep neural networks

1. **Introduction.** Recently, wind power generation has emerged as a renewable energy source. Wind power generation is affected by the weather conditions. Since the weather conditions are not controllable and fluctuating, it is important to predict wind power generation based on weather forecast in order to provide reliably and stably the renewable energy. There are a few studies that predict wind power generation using machine learning and deep learning [1-4]. Predicting wind power generation based on weather forecast has been recently studied using deep learning based methods [5-7].

In this research, a deep neural network (DNN) model is designed to predict wind power generation using weather forecast data. Wind power generation data were collected from a power plant located in Jeju, South Korea, and weather forecast data for the nearby weather stations were collected. The prediction performance of the model was evaluated with root mean square error (RMSE), mean square error (MSE), mean absolute error (MAE), and R-squared (R^2). Experiment results show that the R^2 value ranges from 0.777 to 0.838, RMSE from 224.3kW to 394.3kW, and MAE from 150.6kW to 271.8kW. They are reliable prediction results although their performances are different for each wind power plant.

The remainder of this paper is structured as follows. In Section 2, wind power generation and weather forecast data used in this research are introduced. The prediction process and the design of a DNN model are described in Section 3. The experimental results using the DNN model are presented in Section 4. Finally, we conclude this paper with future work in Section 5.

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2. **Dataset.** To build the prediction model, we use the wind power generation data of Hankyung and Seongsan Wind Power Plants that are provided by Korea Southern Power (KOSPO), and the weather forecast data that are obtained by Korea Meteorological Administration (KMA).

The variables in the dataset are described in Table 1. Wind power generation data were recorded every 10 minutes from January 1, 2014 to December 31, 2017. Three power plants are located in Jeju Island, South Korea, as shown in Figure 1. Hankyung Wind Power Plant is in the west coast of Jeju, while Seongsan Wind Power Plant is in the east coast of Jeju. Each plant has two power generation areas. The area 1 of the Hankyung plant has four 1.5MW wind turbines (totally 6MW), and Hankyung plant's area 2 has five 3MW wind turbines (totally 15MW). Seongsan plant has ten 2MW wind turbines in total (totally 20MW). In the plants, all turbines were manufactured by VESTAS, but their power generation capacities are different. And, the two plants are located in the opposite sea sides as shown in Figure 1. In this research, we use the power generation data of two areas of Hankyung plant, and the merged power generation data of Seongsan plant.

TABLE 1. Dependent and independent variables used for wind power generation prediction

Category	Source	Variable	Description (unit)
Dependent variables	Wind power plant	Hankyung area 1	Wind power generation (KW)
		Hankyung area 2	
		Seongsan generation	
Independent variables	Weather forecast	Temperature	Temperature (°)
		Humidity	Humidity (%)
		Wind speed	Wind speed (m/s)
		Wind direction	Direction (0°-360°)
		Rainfall	Rainfall amount (mm)
		Rainfall probability	Rainfall probability (%)
		Snowfall	Snowfall amount (cm)
		Rainfall type	0: none, 1: rain, 2: rain/snow, 3: snow
		Sea wave	Height of sea wave (m)
		Sky Type	1: clear, 2: slightly cloudy, 3: partly cloudy, 4: overcast

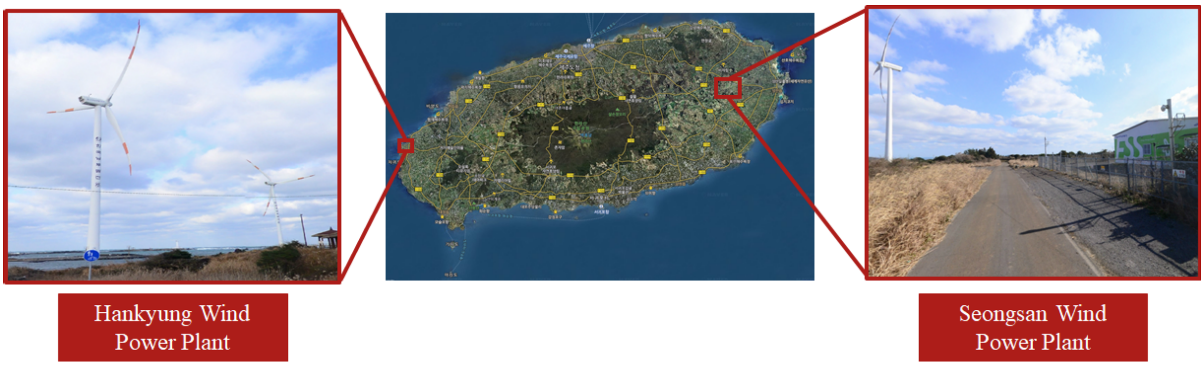

FIGURE 1. Locations of two wind power plants in Jeju Island, South Korea

The KMA announces weather forecast every 3 hours from 2 am (i.e., 8 times per day). Weather forecast data are targeted for 4 hours – 67 hours ahead of the announcement time. In this research, we collected weather forecast data after 4 hours based on announcement time.

3. **Method.** A framework for predicting wind power generation is presented in Figure 2. Data preprocessing consists of three steps. The first step is data grouping. As shown in Figure 3, the wind power generation data are grouped every 3 hours to fit time interval of the wind power generation data and weather forecast data. The second step is feature engineering. Among the weather forecast variables, categorical variables such as *Rainfall Type* and *Sky Type* are one-hot-encoded. The third step is data normalization. To feed the data into the DNN model, it should have a bounded range [8]. All variables are accordingly rescaled into the range of $[0, 1]$ by Equation (1).

$$\widetilde{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

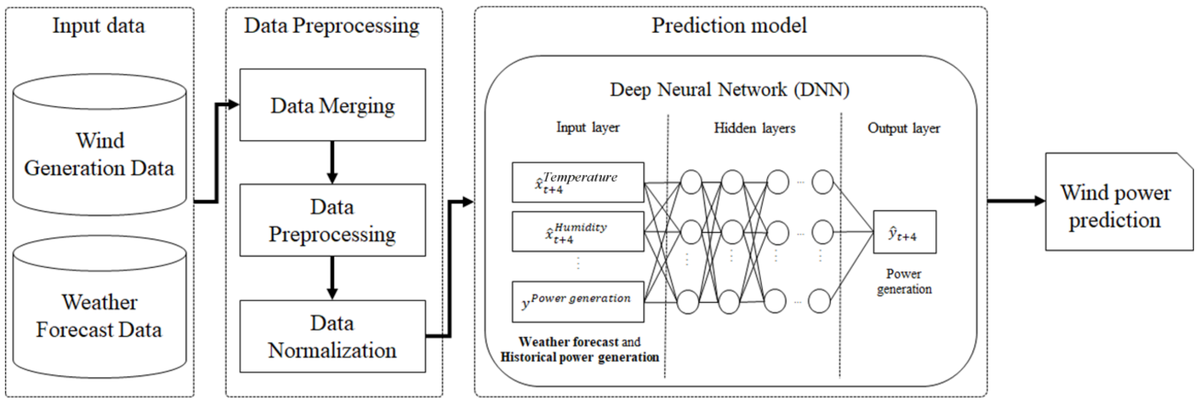

FIGURE 2. System architecture for wind power generation prediction

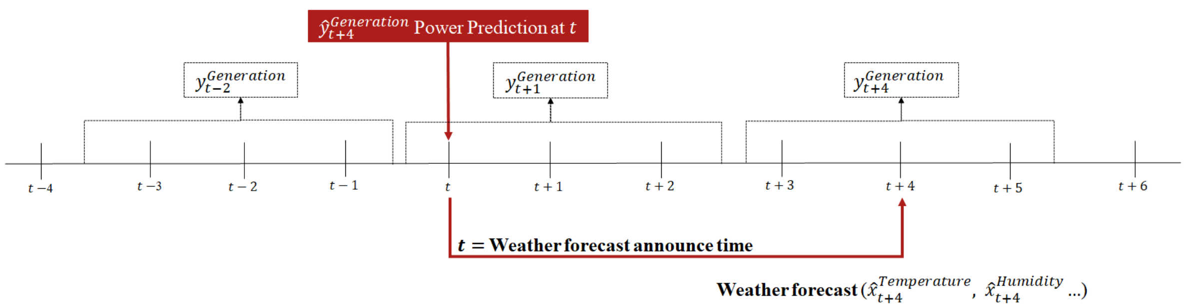

FIGURE 3. Matching weather forecast data and wind power generation data

Figure 4 shows the structure of the DNN model proposed in this paper. In this paper, wind power generation is predicted based on weather forecast data after 4 hours based on weather forecast time t. In the input layer, weather forecast data and historical power generation variables are used. Historical power generation values are added to improve DNN performance. In the hidden layers, layer parameters are set through hyperparameter tuning. The result of hyperparameter tuning is presented in Section 4. Finally, the predicted wind power generation value is calculated in the output layer.

4. **Results.** This section describes the performance of the proposed method presented in Section 3. Table 2 shows the performance of the DNN model. The model is evaluated using four performance measures [9].

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{N}} \tag{2}$$

$$\mathrm{MSE} = \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{N} \tag{3}$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{N} |y_i - \hat{y}_i|^2}{N} \tag{4}$$

$$\mathrm{R}^2 = \frac{\sum_{i=1}^{N} (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \tag{5}$$

y_i is an actual value, $\hat{y}_i$ is a predicted value, $\bar{y}$ is the mean of the actual values, and N is the number of samples. RMSE, MSE, and MAE are error metrics. Figure 5 presents the time series graph for comparing actual and predicted values of DNN model.

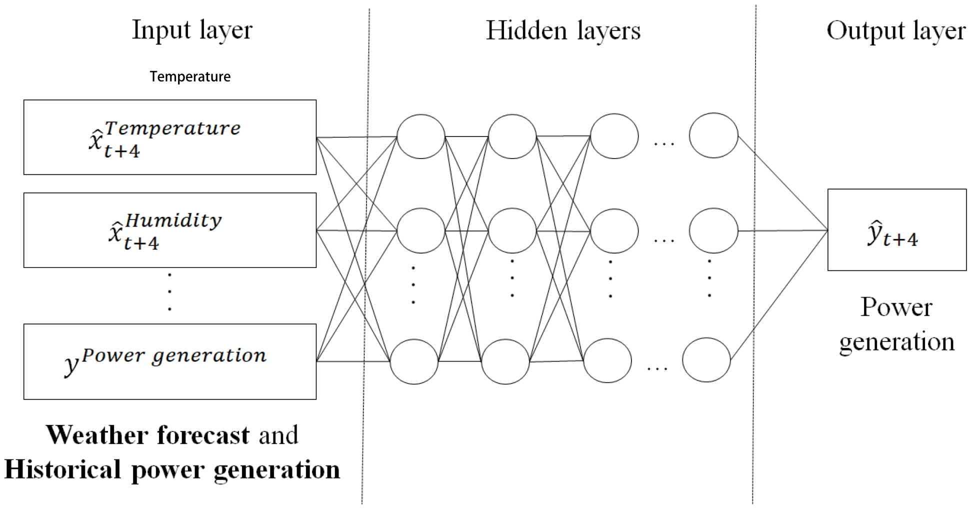

FIGURE 4. Network structure of DNN

TABLE 2. Performances of wind power prediction models

Wind power plant	R^2	MSE (kW)	RMSE (kW)	MAE (kW)
Hankyung area 1	0.818	50304.8	224.3	150.6
Hankyung area 2	0.838	155496.5	394.3	271.8
Seongsan	0.777	97319.5	312.0	220.9

According to Table 2, R^2 values are above 0.7, MSE values range from 50304.8 to 155496.5, RMSE values are from 224.3 to 394.3, and MAE values are from 150.6 to 271.8. The difference in MSE, RMSE, and MAE values for each power plant is presumed to be due to the different total power generation capacity. In Figure 5, although there is not much difference between actual and predicted values, it can be seen that some of the predicted values differ greatly from the actual value at the area 2 of Hankyung power plant. Table 3 shows the result of the hyperparameter tuning for the DNN model. It turns out that a network with two hidden layers, whose number of neurons is 64, and LeakyRelu activation function performs the best among the candidates. The dropout rate of 0.2 is selected. Network training is repeated with 100 epochs, the batch size is 32, and the optimizer is Adam optimizer.

5. **Conclusions and Future Work.** In this paper, we introduced a DNN model for predicting wind power generation based on weather forecast. The performance of the DNN model was evaluated using the KOSPO wind power generation data and KMA weather forecast data. The generated model shows the R-squared value from 77.7% to 83.8%.

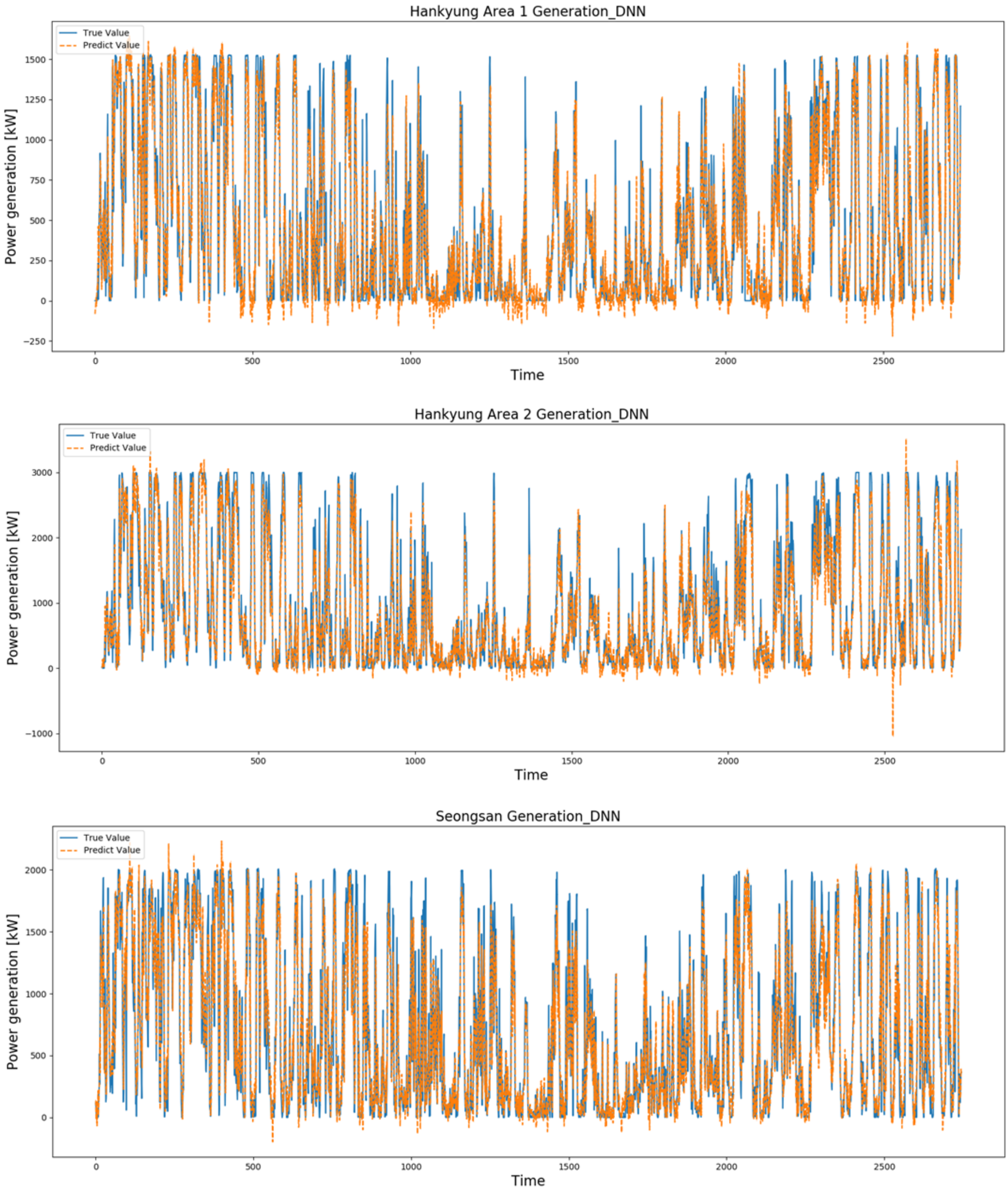

Figure 5. Comparison with actual values and predict values of the DNN model

Table 3. Hyperparameter tuning of the DNN model using the grid search

Hyperparameter	**Candidates**
Number of hidden layers	**2**, 3, 4
Number of neurons	32, **64**, 128
Activation function	Relu, **LeakyRelu**
Dropout	0, **0.2**, 0.5
Optimizer	Adam
Epochs	100
Batch size	**32**, 64

The best values are in underlined boldface.

To improve the prediction performance further, three future work directions can be considered. First, factor analysis would determine the reasons of difference in R-squared values for each area. Second, weather observations beside of weather forecasts can be utilized together. Finally, an ensemble model that concatenates the DNN model introduced in this paper and the model that predicts wind power generation using weather observation data would be able to be developed further.

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