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Support Vector Machine and Long Short-term Memory using Multivariate Models for Wind Power Forecasting

Eun-Ju Kang, Nam-Rye Son

Abstract*: Renewable energy has recently gained considerable attention. In particular, interest in wind energy is rapidly increasing globally. However, the characteristics of instability and volatility in wind energy systems also have a significant on power systems. To address these issues, numerous studies have been carried out to predict wind speed and power. Methods used to forecast wind energy are divided into three categories: physical, data-driven (statistical and artificial intelligence methods), and hybrid methods. In this study, among artificial intelligence methods, we compare short-term wind power using a support vector machine (SVM) and long short-term memory (LSTM). The method using an SVM is a short-term wind power forecast that considers the wind speed and direction on Jeju Island, whereas the method using LSTM does not consider the wind speed and direction. As the experiment results indicate, the SVM method achieves an excellent performance when considering the wind speed and direction.

***Index Terms*: Wind Power Forecasting, Multivariate Models, Support Vector Machine, Long Short Term Memory**

I. INTRODUCTION

Among the different types of renewable energy, wind power has the advantage of relatively low generation costs. However, the power fluctuates significantly as the wind changes, which can affect the power system. To cope with such fluctuations, Europe and the United States are creating forecasts based on meteorological forecasts of flat terrain, and wind facilities are being installed in mountainous areas throughout Japan. Owing to the stochastic nature of wind, wind power differs from conventional thermal power generation. In other words, despite the uncertainty of the output of wind power, it is possible to balance the supply and demand of a power system using a wind power prediction method. The ultimate goal of a wind forecasting model is to predict the wind power as quickly and accurately as possible [1]. As the accuracy of a numerical weather prediction (NWP) model increases and predictive techniques improve, wind power is becoming more useful for power systems and operators [2].

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***** Correspondence Author
Eun-Ju Kang, Dept. Of Information and Communication Engineering, Honam University, Gwang-Ju Korea. Email:ejkang@honam.ac.kr
Nam-Rye Son*, Dept. Of Information and Communication Engineering, Honam University, Gwang-Ju Korea. Email:nrson72@gmail.com

As the proportion of wind power increases, wind forecasting techniques are becoming more important. The more accurate the wind forecast is, the less energy needed to balance the power system and connect the wind power produced. Wind power forecasting techniques make it easier to implement, plan, and deploy thermal power generators, hydro generators, and energy storage devices, and respond more economically in supplying more or less wind power to a power system. The Central Research Institute of Electric Power Industry is developing a weather model, a numerical fluid model, and a statistical model to forecast the weather, accurately forecast the local phase from the results, and improve the output fluctuation prediction technique of wind power plants [3]. We also expect to build a wind power output forecasting system to expand the wind power generation industry, evaluate the characteristics of each component, and develop technologies to verify the complete system.

For this reason, it is extremely important to predict the output of a wind turbine in consideration of the stability of a wind power generation system. The models used for forecasting the wind power can be classified into three types: physical methods, data-driven methods (statistical and artificial intelligence), and hybrid methods. (1) Physical methods predict the wind power using mathematical modeling, considering the weather data (e.g., air pressure map, and jet stream) and environmental characteristics (e.g., temperature, humidity, topography, and land use) [4]. (2) Data-driven methods predict the wind speed within a few hours through a pattern analysis, and are trained based on past data. Such methods are more suitable for forecasting wind speed values within a short period of time because the amount of past data continuously increases [5]. (3) Hybrid methods employ a prediction approach through the application of a statistical prediction after acquiring weather forecast data using physical methods and a combination of both physical and statistical approaches [6]. Each of the three methods mentioned above has its own advantages and disadvantages.

However, the most important factors in short-term wind power forecasting are the use of certain variables (e.g., wind power, wind direction, wind speed, and meteorological factors) and the application of learning algorithms (e.g., NWP, statistical algorithms, autoregressive integrated moving average, machine learning, and a deep neural network). Previous studies have considered two factors in short-term wind forecasting [11, 12]. The present study compares the performances of existing research.

The learning and test data used in this study are wind power, wind direction, and wind speed collected from Jeju A, B, C wind farms.

The remainder of this study is organized as follows. In Section 2, we describe the SVM applied using a multivariate model and LSTM using a hybrid model. Section 3 analyzes the experimental environment and results for wind farms A, B, and C on Jeju Island. Finally, Section 4 provided some concluding remarks and areas of future study.

II. RELATED STUDIES

A. SVM using Multivariate Model

Four models combining wind power, wind direction, wind speed, and a variation of wind power for short-term wind forecasting were adopted [7]. Model 1 uses wind power, wind direction, wind speed, and a variation of wind power. Model 2 uses wind power, wind direction, and wind speed. Model 3 uses wind power, wind speed, and a variation of wind power. Finally, model 4 uses wind power, wind direction, and a variation of wind power. To select the best of the four models, a support vector regression (SVR) was adopted using Eq. (1), along with Gaussian kernel as shown in Eq. (2).

$$\begin{aligned} &\min . \frac{1}{2}\left\|\omega^{2}\right\|+C \sum_{i=1}^{m}\left(\xi_{i}+\xi_{i}^{*}+v \varepsilon\right) \\ &s.t. \quad y_{i}-\left(<w, \phi\left(x_{i}\right)>+b\right) \leq \varepsilon+\xi_{i} \\ &\qquad \left(<w, \phi\left(x_{i}\right)>+b\right)-y_{i} \leq \varepsilon+\xi_{i}^{*} \\ &\qquad \xi_{i}, \xi_{i}^{*}, \varepsilon \geq 0, i=1, \ldots, m \end{aligned} \tag{1}$$

In Eq. (1), x is the input vector, y is the output vector, ω is the coefficient vector, b is bias, ξ_i and ξ_i^* are the slack used for a conditional relaxation, and C is the penalty parameter or unit cost.

$$K(x, y)=\exp\left(-\gamma\|x-y\|^{2}\right) \tag{2}$$

The Gaussian kernel moves the data to an infinite dimension and returns the same result as in computes the dot product there [16].

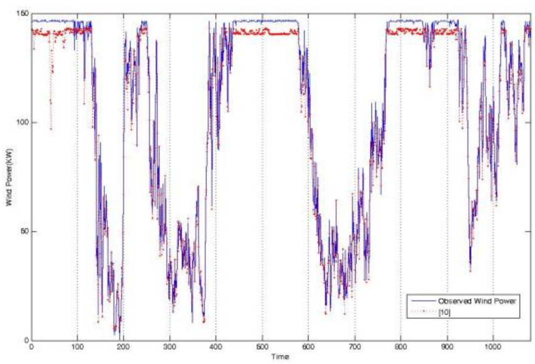


Fig.1. Wind power forecasting using an SVM with a multivariate model

As a result, model 2 achieved the best performance for a short-term wind forecasting. However, it has a disadvantage of rapid changes in the area where the wind power does not change, as shown in Fig. 1. As the reason for this, the SVM was performed by looking at the wind power, wind direction, and wind speed without reflecting the time series, which is a data characteristic of wind power. As a disadvantage of the previous study [7], this study extracts the wind direction and wind speed, which are characteristics of the wind [8]. Model 2 reflects the characteristics of the time series data and predicts the short-term wind power based on the SVM. A correlation analysis and clustering were conducted to extract feature vectors of the wind direction and speed. The correlation analysis is based on Pearson's [9] and Spearman's correlation analyses of the wind power, wind direction, and wind speed [10]. As a result, the wind power forecasting accuracy is improved by applying the nonlinear relationship between the wind direction and speed.

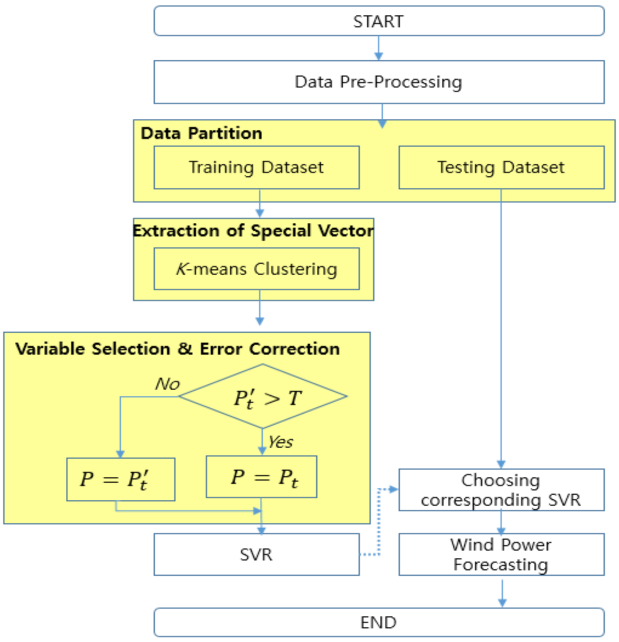


Fig.2. Flowchart of wind power forecasting using SVM with a multivariate model

The SVM using a multivariate model [11] is proposed to overcome the shortcomings of previous studies [7, 8]. Wind power prediction using the SVM along with a multivariate model process is shown in Fig. 2 and in the following:

- **Data pre-processing**: The wind power, speed, and direction data units generated by the wind farm are different, and a data pre-processing is required. In this study, the min-max normalization method was adopted as shown in Eq. (3) [17].

$$v_{i}^{'}=\frac{v_{i}-\min_{A}}{\max_{A}-\min_{A}}\left(w\_\max_{A}-w\_\min_{A}\right)+w\_\min_{A} \tag{3}$$

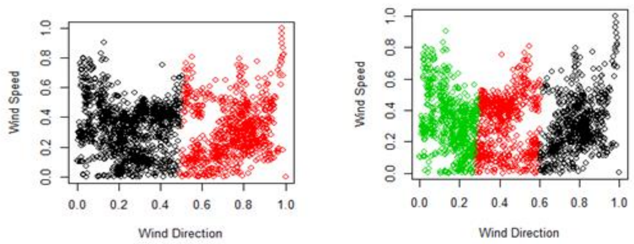
where min_A and max_A are the minimum and maximum values of property A, respectively, and value v_i of A is placed into value $v_i^{'}$ within the range of [min_A, max_A].

- **Data partition**: The data on the wind farms in areas A, B, and C of Jeju Island are divided into learning and test data to predict the short-term wind power.
- **Extraction of special vector**: *K*-means clustering [14] is used to extract the feature vectors of the wind direction and speed, as shown in Eq. (4):

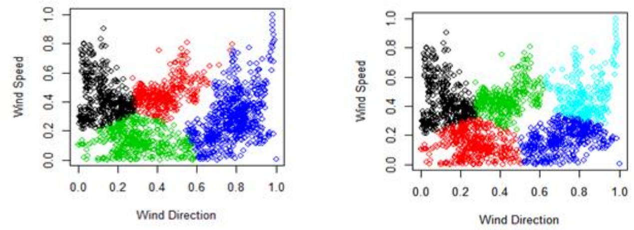
$$\arg\min_{S} \sum_{i=1}^{k} \sum_{x \in S_i} \| x - \mu_i \| \tag{4}$$

where $S = \{S_1, S_2, .., S_k\}$ and μ_i is the mean of the points in S_i.

Fig. 3 shows the results of clustering using the wind speed and direction of the wind farm in region A of Jeju Island. Fig. 3(a) shows two clusters, Fig. 3(b) shows three clusters, Fig. 3(c) shows four clusters, and Fig. 3(d) shows five clusters. The number of clusters is influenced by the wind direction.



(a) Two clusters **(b) Three clusters**



(c) Four clusters **(d) Five clusters**

Fig.3. Clustering using wind direction and speed

- **Variable selection and error correction**: If the fluctuation in wind power is greater than the threshold, there is no continuous-time characteristic, and thus only the learning data of the wind direction, wind speed, and wind power are used in the SVR. By contrast, if the fluctuation in wind power is less than the threshold, it has a continuous-time characteristic, and only the learning data of the wind direction, speed, and power, and the fluctuation in wind power, are applied in the SVR.
- **Test**: The SVR is applied to the learning and the short-term wind power is predicted by applying the proposed method to the test data for areas A, B, and C of Jeju Island.

B. LSTM using Hybrid Model

LSTM is an artificial recurrent neural network architecture used in the field of deep learning [13], and is applied to tasks such as unsegmented, connected handwriting recognition, and speech recognition. Fig. 4 shows the structure of LSTM, where the LSTM cells are computed through Eq.(5), where i_t, f_t, and O_t are the input, forget, and output gates, respectively, and $\tilde{C}_t$ is a new candidate value for the cell state. The LSTM cell acts as an accumulator of the state information, and an update of the old cell state C_{t-1} into the new cell state C_t is applied. In addition, W_i, W_f, W_o, and W_c are weights of the input, forget, output, and current cell states, respectively, and b_i, b_f, b_o, and b_c are the biases of the input, forget, output, and current cell states, respectively.

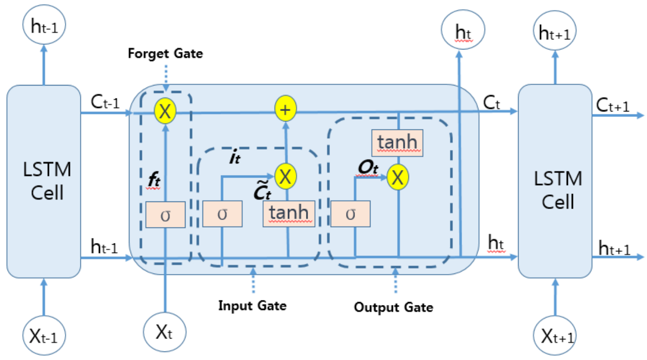
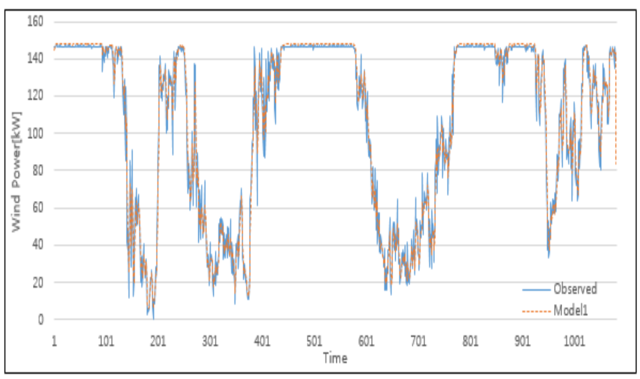


Fig.4. Structure of LSTM

$$\begin{aligned}
i_t &= \sigma(W_i \times [C_{t-1}, h_{t-1}, X_t] + b_i) \\
\tilde{C}_t &= \tanh(W_c \times [C_{t-1}, h_{t-1}, X_t] + b_c) \\
f_t &= \sigma(W_f \times [C_{t-1}, h_{t-1}, X_t] + b_f) \\
C_t &= f_t \times C_{t-1} + i_t \times \tilde{C}_t \\
O_t &= \sigma(W_o \times [C_t, h_{t-1}, X_t] + b_o) \\
h_t &= O_t \times \tanh(C_t)
\end{aligned} \tag{5}$$

In [12], four multivariate models for wind power forecasting are used. M1 indicates the wind power, M2 indicates the wind power and direction, M3 is the wind power and speed, and finally M4 is the wind power, speed, and direction. Fig. 5 shows a comparison of the wind power forecasting by models using LSTM in region A of Jeju Island.

Fig. 5(a) shows that the predicted value is similar to the measured value at the initially, but the predicted value toward deviated from the observed value toward the midpoint. Fig. 5(b) shows that the predicted value is higher than the observed value initially, but the predicted value is similar to the observed value toward the midpoint. Finally, Figs. 5(c) and 5(d) show that the predicted value is lower than the observed value initially, but the predicted and observed values become similar from the midpoint.



(a) Comparison of observed value with model 1

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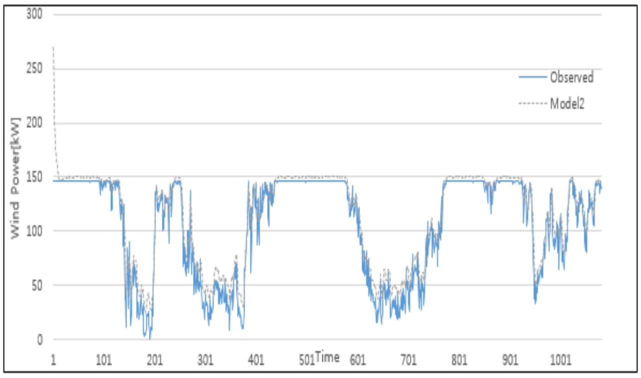
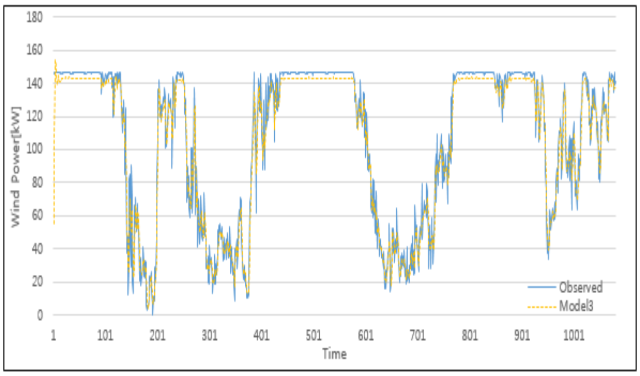
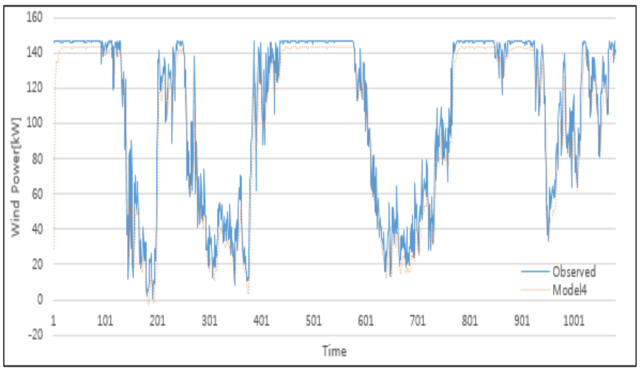


(b) Comparison of observed value with model 2



(c) Comparison of observed value with model 3



(d) Comparison of observed value with model 4

Fig.5. Comparison of observed and predicted values based on the models used

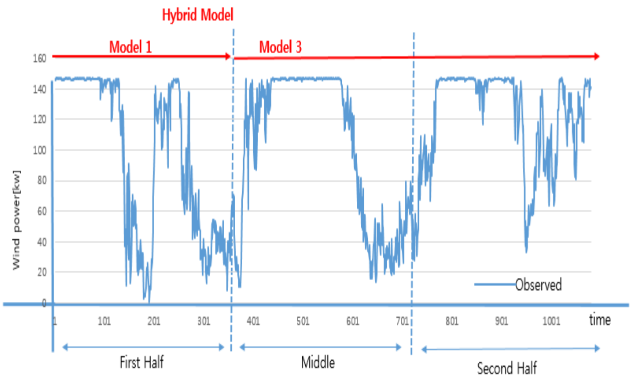


Fig.6. Wind power forecasing using LSTM with the hybrid model

Therefore, the hybrid forecasting model combines M1 and M3 with the smallest prediction error for each model, as shown in Fig. 6 [15]. That is, when experimenting with the learning and testing of the proposed hybrid forecasting model, M1 is used initially (during the first half), and M3 is applied from the midpoint until the end of the process.

III. TEST AND RESULT

A. Test Environment and Performance Metrics Used for Evaluation

To verify the proposed method, experiments were conducted on a PC equipped with an Intel Xeon (R) W-2133, 3.60 GHz CPU, and 32 GB of RAM. Windows 10 (64 bit) was used as the test operating system, and MATLAB R2019a was applied as the experimental program. The root mean square error (RMSE) and mean absolute error (MAE) were used to verify the wind power prediction error, as shown in Eq. (6).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i - \hat{p}_i)^2} \qquad (6)$$

$$MAD = \frac{1}{n}\sum_{i=1}^{n}\left|p_i - \hat{p}_i\right|$$

where p_i and $\hat{p}_i$ are the observed and predicted values respectively, and n is the number of learning models.

B. Dataset

In this study, the learning and testing data were tested based on the wind power, direction, and speed, which were collected from wind farms in regions A, B, and C on Jeju Island to predict the short-term wind power in 2014. At this time, the learning and test data are all normalized, and the collection period, collection time, learning data, test data, and total data are applied for each region, as shown in Table 1.

Table 1. Collection period, time, learning and test data

Region	Period	Time	Learning Data	Test Data	Total Data
A	01.11~ 01.25	10min	1,080	1,080	2,160
B	01.11~ 01.20	10min	1,008	432	1,440
C	01.11~ 01.25	10min	1,440	720	2,160

C. Comparison and analysis of SVM and LSTM

Table 2 shows the difference in performance between the SVM using a multivariate model [11] and LSTM using the hybrid model [12] for short-term wind power forecasting in areas A, B, and C of Jeju Island.

Table 2. Comparison of short-term wind power prediction

Region	SVM using multivariate Model[11]		LSTM using hybrid Model[12]	
	RMSE	MAD	RMSE	MAD
A	3.1	2.1	3.7	2.6
B	1.4	1.0	3.4	2.5
C	2.6	1.7	5.6	4.2

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In calculation complex, the SVM using a multivariate model [11] takes longer to compute than the LSTM using the hybrid model [12] because it uses *k*-means clustering to extract the wind characteristics of the wind direction and speed.

With the RMSE and MAD, the SVM using a multivariate model [11] seems to outperform the LSTM using a hybrid model [12]. With the RMSE, the SVM using a multivariate model is superior to LSTM using hybrid model by 0.6, 2.0, and 3.0 per region. Specifically, the performances of the SVM using a multivariate model [11] and LSTM using the hybrid model [12] are not very different in region A, but the difference in performance is large in regions B and C.

Figs. 7 and 9 show the performance comparison of the SVM using a multivariate model and LSTM using the hybrid model for the observed value. The SVM using a multivariate model predicts the short-term wind power similarly to the observed value.

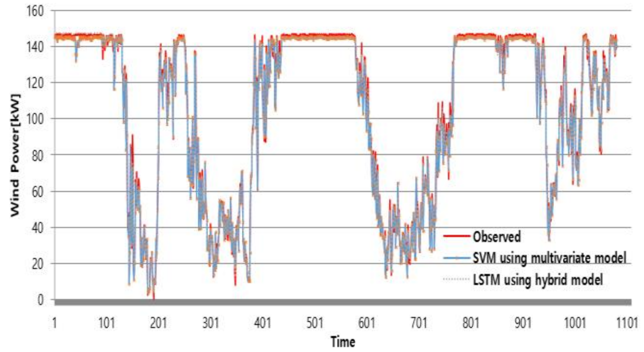

Fig.7. Comparisons between the SVM using a multivariate model and LSTM using the hybrid model in region A of Jeju Island

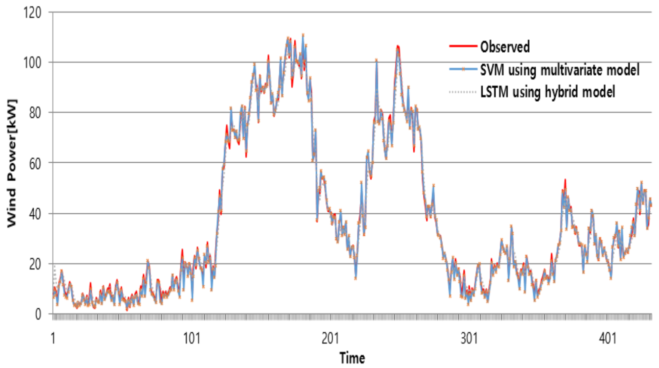

Fig.8. Comparisons between the SVM using a multivariate model and LSTM using the hybrid model in region B of Jeju Island

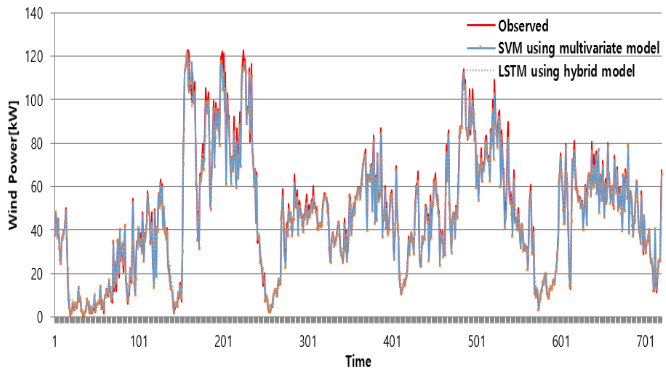

Fig.9. Comparisons between the SVM using a multivariate model and LSTM using the hybrid model in C region of Jeju Island

IV. CONCLUSION AND FUTURE WORK

In this study, we compared the performances of the SVM using a multivariate model and LSTM using the hybrid model. The SVM and LSTM are representative algorithms for machine learning and deep learning, respectively. (1) The SVM using a multivariate model extracts the features when considering the wind direction and speed. (2) LSTM using the hybrid model combines the merits of the multivariate models. M1 (wind power) was adopted initially and M3 (wind power and wind speed) was applied from the midpoint to the end of the process. Experimental results show that the SVM using a multivariate model outperforms LSTM using the hybrid model. However, we know that the variables of the multivariate model are important for both of the proposed methods. Future research in short-term wind power forecasting will be extended to other regions in Korea and overseas.

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AUTHORS PROFILE

Eunju Kang, received her BS degree in mathematics education from Seoul National University in 1985, and her MS degree in mathematics from Seoul National University in 1987. She received her PhD in mathematics from Seoul National University in 1995. She is currently an associate professor in the Department of Information and Communication Engineering at Honam University.

Namrye Son, received her BS degree in computer science and statistics from Honam University in 1996, and her MS degree in computer science and statistics from Jeonnam National University in 1999. She received her Ph.D. in computer science from Jeonnam National University in 2005. She is currently an assistant professor in the Department of Information and Communication Engineering at Honam University.