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Meteorological Factor Multivariate Models Affecting Solar Power Prediction using Long Short-term Memory

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Abstract*: Solar power systems have been recently installed in buildings to efficiently manage their energy consumption and production in them. Because electrical energy is produced and consumed simultaneously owing to its physical nature, it is necessary to predict the exact solar power necessary to maintain a stable power supply. To manage the building energy management system (BEMS) effectively, this paper proposes 6 models (solar radiation, sunlight, humidity, temperature, cloud cover, wind speed) and compares the performances of these models. Through this comparison, we solved the traditional long short-term memory (LSTM) problem and proposed a new LSTM. It was determined that the meteorological factors for forecasting solar power varied by season. The performance was shown in order of solar radiation, sunshine, wind speed, temperature, cloudiness and humidity at annual average. Additionally, the proposed LSTM performed better than the traditional LSTM.

***Index Terms*: Solar Power Prediction, Meteorological Factor, Long Short-term Memory, Building Energy Management System**

I. INTRODUCTION

Korea has recently announced the "Implementation Plan for Renewable Energy 3020" which aims to promote the use of renewable energy. "Implementation Plan for Renewable Energy 3020" is a plan to foster solar, offshore wind, and hydrogen fuel cells and increase the proportion of renewable energy usage, which was 8.08% in 2017, to 20% by 2030. The total sales of renewable energy companies in 2017 was about approximately 9.6 trillion won, 6.4 trillion won 67% of which was from solar power. Solar power use is expected to continue to grow as it has the fastest rate of decline in power generation costs among renewable energy sources and is the most effective resource for expanding small-scale distributed power sources.

In addition, the government will continue to support solar operators [1, 2]. The solar power system that operates this solar power is used in areas such as homes, buildings, and factories. Areas energy management system is divided, according to usage, into home energy management system (HEMS), building EMS (BEMS), and factory EMS (FEMS). BEMS is a system of computer-aided tools used by operators of electric utility grids to monitor, control, and optimize the performance of the generation or transmission system.

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Despite the various advantages of BEMS, it is problematic because energy is required to supply stable power because it is produced and consumed at the same time due to its physical characteristics [3, 4].

To supply stable power, solar power prediction methods have been divided into three categories: physical methods, data-driven methods and hybrid methods [5].

(1) Physical methods predict solar power generation by utilizing solar module datasets, weather data (e.g., air pressure maps, the jet stream), and environmental characteristics (e.g., temperature, humidity, topography, land use) [6].

(2) Data-driven methods pair a set of data (e.g. historical solar power data, meteorological data, and etc.) to a mapping function which forecast solar power generation. The traditional approach uses the time series for prediction, such as the auto-regression moving average (ARMA) [7], artificial neural networks (ANN) [8], particle swarm optimization (PSO) [9], support vector machine (SVM) [10], and so on.

(3) Hybrid methods were proposed in recent years to combine the advantages of the former two groups. Hybrid methods can be categorized into four types [11-13]: weight-based combined approaches [14], data preprocessing based combined approaches [15], parameter selection and optimization based combined approaches [16], and data post processing based combined approaches [17].

This paper details a comparative study of six models created by combining meteorological factors (i.e., solar radiation, sunlight, humidity, temperature, cloudiness, wind speed) that affect solar power prediction. The performance between models required the creation of a new LSTM by modifying traditional LSTM among data-driven methods. This is because the traditional LSTM uses the value of the previous prediction when forecasting the solar power in the time step between two predictions. This is disadvantageous because the predicted value of solar power is continuously increased whenever the previous predicted value is wrong. In comparison, the proposed LSTM can access the observed value of the time step between two predictions, so it predicts the solar power by updating the network status using the observed value instead of the predicted value.

The composition of this paper is as follows. Section 2 describes factors affecting solar power prediction and LSTM among deep learning. Section 3 proposes a modified LSTM. Section 4 introduces the test environment including the test data set and analyzes the multivariate models by 12 months. Finally, Section 5 presents the conclusions and proposes future work.

II. RELATED WORK

A. Factors Affecting Solar Power Prediction

Factors influencing solar power can be classified into meteorological, geographical, and facility factors [18]. First, meteorological factors include solar radiation, sunshine, ultraviolet rays, temperature, cloudiness, rainfall, snowfall, dust, fine dust, humidity, wind direction and wind speed. Of these, solar radiation has the biggest influence on solar power. The reason is that the principle behind solar power is solar radiation, which is the radiation of light from the sun when the sun's light energy is converted into electricity. In addition, because the solar cells constituting the module of the solar power system are semiconductors, the efficiency is lower at high temperatures, making the temperature another factor affecting the solar power.

Other meteorological factors include sunshine hours, cloudiness, humidity, wind direction, wind speed, rainfall, snowfall, yellow dust, and fine dust, etc. Second, geographical factors mean that different power plants do not produce the same amount of power, even though they experience similar weather conditions.

This means that geographical factors in addition to meteorological factors affect solar power. Geographical factors include latitude, longitude and altitude. Finally, equipment factors are classified into fixed type, fixed variable type, and tracking type.

The reason for this is that the solar power differs according to the inclination angle of the solar cell module of the photovoltaic power generation system. In addition, the efficiency of the battery and power converter will affect the solar power.

In this paper, we selected only the meteorological factors, because the geographical and equipment factors are fixed.

B. Recurrent Neural Network

The existing neural networks, feed-forward neural networks (FFNets), process each input and output independently. In other words, when data are input, operations progress sequentially from the input layer to the hidden layer, and output is provided to the output layer. In this process, the input data are limited in that all nodes can be executed only once.

However, the RNN exhibits excellent performance in a system that predicts the following states because the same process is repeated for all the input data, and the current data and all previous calculation information are applied to the current prediction result.

Thus, RNNs are applied to areas with outstanding performance in continuous data processing, such as speech recognition, translation, language modeling, video data, log data, and time series statistical data [19].

Fig. 1 shows the RNN structure where the output of the hidden layer is input to the hidden layer again. *Eq*. (1) is the model expression used in the hidden layer.

$$H_t = \tanh(W_x \times X_t + W_h \times H_{t-1})$$
$$Y_t = \sigma(W_x \times H_t) \quad (1)$$

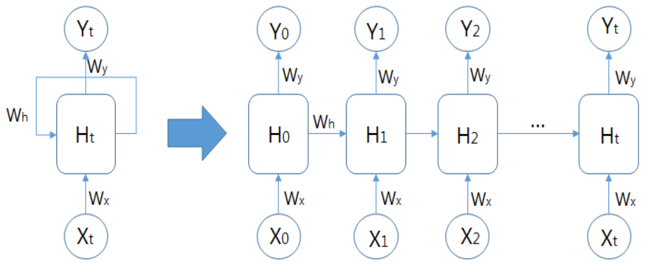


Fig.1 Structure of Recurrent Neural Networks

In *Eq*. (1), H_t and Y_t are the state values of the hidden layer and the output values of the output layer, respectively, at time *t*. W_x is a weight from the input layer, and W_h is a weight for H_{t-1}, which is the hidden state value of the previous time $t-1$ and represents one of the nonlinear activation functions, whereas the hyperbolic tangent function (*tanh*) is used to calculate H_t. Y_t is calculated using the sigmoid (σ) function for the hidden layer state value and output layer weight at time *t*.

C. Long Short-term Memory

The RNN has a problem of needing to learn data over a long period of time with a vanishing gradient where past learning results disappear if the time interval is large. To solve these drawbacks, Hochreiter proposed LSTM in 1997. As shown in Fig. 2, the LSTM is a cell stat in addition to the hidden state. C_t is the cell state at time t [20].

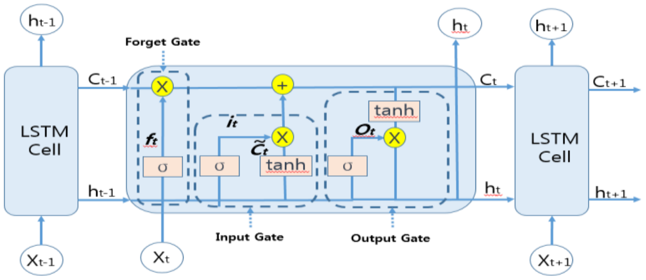
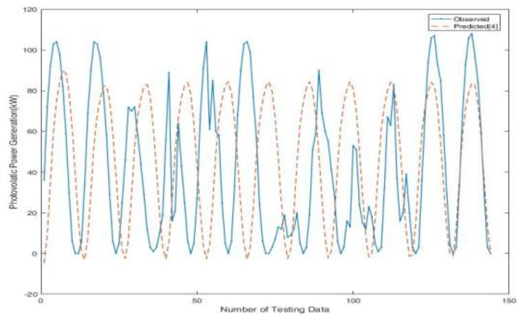


Fig.2 Structure of Long Short-term Memory

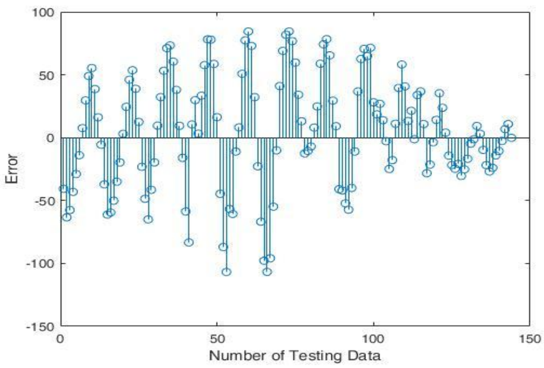
The cell state is also used as an input to obtain the cell state at the next time point, such as the previously learned hidden state. We use three gate layers (Input, Forget, and Output) to obtain the hidden state value and the cell state value. These three gates commonly use the sigmoid (σ) function to adjust the gate according to the values of 0 and 1.

III. PROPOSED METHOD

Fig. 3(a) shows solar power prediction using traditional LSTM, which uses the value of the previous prediction when predicting the solar power value at the time step between the prediction and the prediction. As shown Fig. 3(b), if the predicted value is wrong, the predictive value of solar power is continuously increased as well as the error of prediction. Therefore, in this paper, because the observed value of the time step between two predictions can be determined through the following four steps, the solar power is predicted by updating the network state using the observed value instead of the predicted value.



(a) Comparison of observed and predicted value



(b) Error of prediction

Fig. 3 Solar Power Prediction using Traditional Long Short-term Memory

A. Input Gate Layer

It receives information from previous hidden layer and the current input. Then computers obtain an output with the following *Eq*. (2).

$$\begin{aligned} i_t &= \sigma(W_i \times [C_{t-1}, h_{t-1}, X_t] + b_i) \\ \tilde{C}_t &= \tanh(W_c \times [C_{t-1}, h_{t-1}, X_t] + b_c) \end{aligned} \quad (2)$$

where i_t is the output of input gate, X_t and h_{t-1} are the current input and previous hidden layer output, respectively. b_i and b_c are the bias of the input gate and bias for $\tilde{C}_t$. σ is the activation function and a soft function is adopted in this paper as shown *Eq*. (3).

$$\sigma_{softsign}(x) = \frac{x}{1+|x|} \quad (3)$$

B. Forget Gate Layer

The output of the forget gate has a similar computation formula as the input gate with different weights W_f and bias b_f as shown in *Eq*. (4).

$$f_t = \sigma(W_f \times [C_t, h_{t-1}, X_t] + b_f) \quad (4)$$

C. Cell State Update

The update step from the previous cell state (C_{t-1}) to the current cell state (C_t), is shown in *Eq*. (5).

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \quad (5)$$

D. Output Gate Layer

Its result is determined by the current input, the current memory and the previous hidden layer output. The calculation formulas are described in *Eq*. (6).

$$\begin{aligned} O_t &= \sigma(W_o \times [C_{t-1}, h_{t-1}, X_t] + b_o) \\ h_t &= O_t \times \tanh(C_t) \end{aligned} \quad (6)$$

where O_t, h_t and b_0 denote the outputs of the gate, the current hidden layer and bias for O_t, respectively.

IV. RESULT AND DISCUSSION

A. Test Environment

To verify the proposed method, experiments were performed on a PC equipped with Intel Xeon (R) W-2133 3.60GHz CPU and 32GB RAM. The test operating system was Windows10 (64bit) and the experimental program was MATLAB R2019a. Finally, root mean square error (RMSE) and mean absolute error (MAE) were used as statistical methods to verify the solar power prediction error as shown in *Eq*. (7).

$$\begin{aligned} RMSE &= \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i - \hat{p}_i)^2} \\ MAE &= \frac{1}{n}\sum_{i=1}^{n}\left|p_i - \hat{P}_i\right| \end{aligned} \quad (7)$$

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

B. Multivariate Models and Test Dataset

In this paper, to verify the usefulness of the proposed method, we collected data on buildings located in Ansan City, Gyeonggi Province from April 2018 to March 2019 in 1 hour increments. The main purpose of this building which have a total area of 1,980m^2, is power exchange. The building structure includes H-BEAM and sandwich panel for outer walls. The PV system capacity is 150 kW. The PCS and battery capacity are 250 kW and 550 kW, respectively. The meteorological data is the data of Suwon area in Gyeonggi province which is closest to the meteorological observation point.

Table 1 shows six multivariate models (M1~M6) that are defined by combining data of solar power and meteorological data in this paper.

Table 1. Multivariate Models

No	Factors
Model 1 (M1)	Solar Power, Solar Radiation
Model 2 (M2)	Solar Power, Sunlight
Model 3 (M3)	Solar Power, Humidity
Model 4 (M4)	Solar Power, Temperature
Model 5 (M5)	Solar Power, Cloud Cover
Model 6 (M6)	Solar Power, Wind Speed

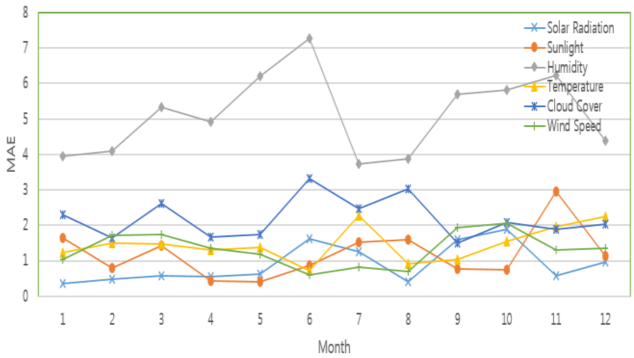
Table 2. Comparison for Meteorological Factors Affecting Solar Power

No \ Month	2018									2019		
	4	5	6	7	8	9	10	11	12	1	2	3
M1	0.64	0.79	1.70	1.37	0.52	1.63	1.91	0.74	1.09	0.41	0.54	0.69
M2	0.55	0.47	0.89	1.90	1.69	0.84	0.81	3.08	1.17	1.66	0.86	1.44
M3	6.85	9.44	12.48	4.80	5.22	7.37	7.76	9.09	5.81	5.52	5.76	7.87
M4	1.63	1.92	0.91	2.56	1.22	1.33	2.17	2.34	2.55	1.56	2.06	1.82
M5	2.18	2.37	4.08	3.03	3.30	2.02	2.73	2.61	2.92	3.09	2.08	3.24
M6	1.54	1.42	0.79	0.98	0.91	2.16	2.76	1.56	1.86	1.36	1.96	2.22

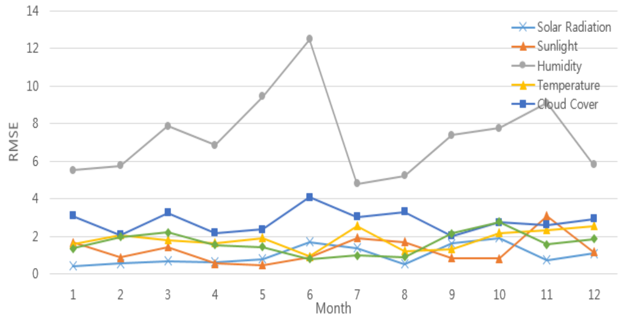
C. Results for Meteorological Factors Affecting Solar Power

Learning and testing data were divided into 80% and 20%, respectively. The hidden layer of LSTM consisted of 200 blocks, the initial learning rate was fixed at 0.005 and the maximum number of iterations was fixed at 50.

Table 2 and Fig. 4 show the comparison for meteorological factors affecting solar power prediction from April 2018 to March 2019 using RMSE. Fig. 4(a) and 4(b) show the MAE and RMSE error measurement results for meteorological factors affecting solar power by models, respectively. The meteorological factor values vary slightly depending on the error measurement results, and experimental results show that the meteorological factors affecting solar power prediction are in descending order as follows: M1 (solar radiation), M2 (sunshine), M6 (wind speed), M4 (temperature), M5 (cloud cover), M3 (humidity). Solar radiation has the greatest influence on solar power while humidity does not affect solar power prediction.



(a)MAE



(b) RMSE

Fig.4 Meteorological Factors Affecting Solar Power Determined by the Models

As Fig. 4 shows, the models are sometimes unable to predict the solar power due to abnormal climate conditions in Korea. As an example of the effects of climate change in Korea, the spring and fall periods have been reduced, whereas the summer and winter periods have become longer. The rainy season in Korea usually starts at the end of June, but recently, it has been starting in July. Even if the rainy season begins as normal, the solar power cannot be accurately predicted due to various uncertain weather conditions, such as a dry rainy season and heavy rains. Usually, during the rainy season (June to July), humidity is thought to have a considerable influence on solar power forecasting, but it seems to have less influence than the other meteorological factors. In spring and autumn, when the sunlight is strongest, both solar radiation and sunlight have a remarkable influence on the prediction of solar power.

However, in November, the sunlight value is more prone to error than the other meteorological factors. The reason for this is not only because there is more cloud cover than sunshine but also because the sunlight throughout the Ansan area seems to be quite irregular.

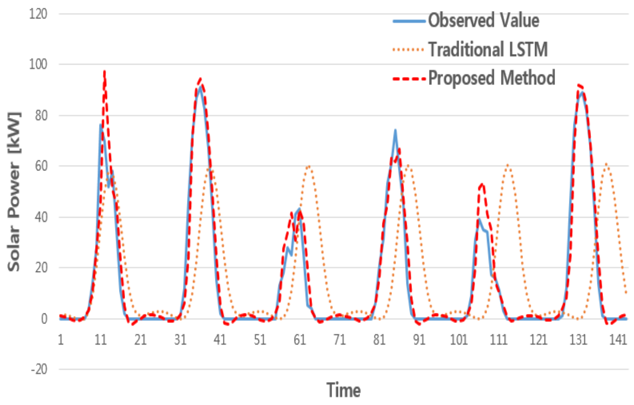
D. Comparison Performance of Traditional and Proposed LSTM

Table 3 compares the annual average RMSE, MAE, and computation times of the traditional LSTM and the proposed LSTM. Although the complex time of traditional LSTM is almost similar to that of the proposed LSTM, the minimum complex time order for each model is M6, M5, M4, M3, M2, and M1. Finally, the RMSE and MAE of proposed LSTM are superior to the traditional LSTM.

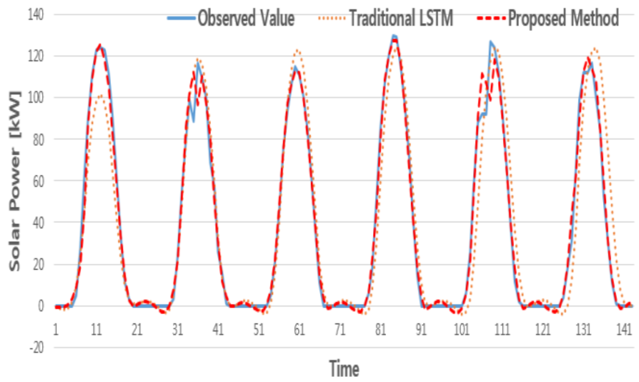
Fig. 5 depicts the comparisons of solar power prediction between the traditional and proposed method for observed data. It is a comparison of the results for the representative spring, summer, fall, and winter owing to the characteristics of Korean weather. As shown in Fig. 5, we can see the predicted value is almost similar to observed value. The observed values for spring, summer, and winter maintain a consistent pattern, whereas the autumn observed values exhibit a non-random pattern. Traditional methods do not accurately predict solar power in other seasons except summer. However, the proposed method yielded similar predictions to the observations regardless of the season.

Table 3. Comparison of RMSE, MAE, Computation Time for traditional and Proposed LSTM by Models

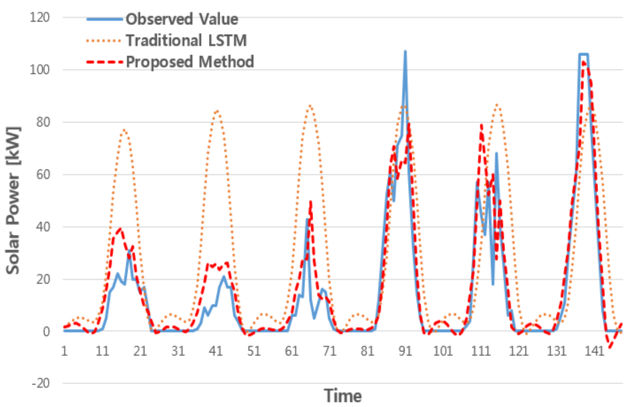
No	RMSE			MAE			Computation Time(sec)
	Traditional	Proposed	Difference	Traditional	Proposed	Difference	
M1	36.16	1.00	-35.16	25.23	0.91	-24.32	101.34
M2	36.23	1.28	-34.95	25.26	1.19	-24.07	94.02
M3	50.11	7.33	-42.78	42.60	5.12	-37.48	86.90
M4	28.13	1.84	-26.29	20.52	1.47	-19.05	81.94
M5	32.61	2.80	-29.81	23.37	2.19	-21.18	77.60
M6	32.33	1.63	-30.70	19.97	1.31	-18.66	74.09



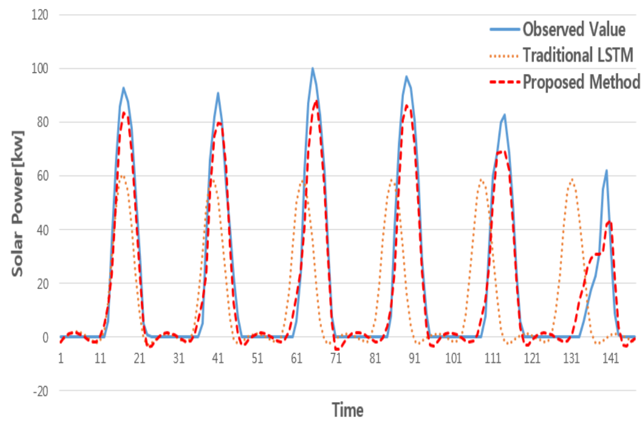
(a) Comparison of traditional and proposed methods for April 2018 (Spring)



(b) Comparison of traditional and proposed methods for August 2018 (Summer)



(c) Comparison of traditional and proposed methods for November 2018 (Fall)



(d) Comparison of traditional and proposed methods for January 2019 (Winter)

Fig.5 Comparison of Solar Power Prediction using Traditional and Proposed Long Short-Term Memory

V. CONCLUSION

Korea has recently launched government-led, low-carbon green growth policies that are being pursued in various ways to reduce energy consumption. Among them, studies on energy saving of buildings using ESS, BEMS, etc. are underway. Therefore, herein, we propose a solar power prediction method to efficiently manage BEMS using LSTM which is a deep learning technology for efficient building energy operation. At this time, we experimented based on meteorological factor data which have the greatest influence on the prediction of solar power. Experimental results show that the meteorological factors affecting solar power are, in descending order of impact, solar irradiation, sunshine, wind speed, temperature, cloudiness, and humidity. In comparison with traditional LSTM, the proposed LSTM can accurately predict solar power. In future research, we will test the proposed LSTM by expanding it to 22 models by combining the 6 models proposed herein. Additionally, we will forecast solar power in units of medium-term (month) as well as long-term (annual) using the proposed LSTM.

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