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Prediction Model of Wind Speed and Direction Using CNN and CLSTM with Vector Image Input

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Abstract

We describe a wind speed prediction method using wind vector images as input. The prediction model combines convolutional neural network (CNN) and convolutional long short-term memory (CLSTM), which are effective for image analysis. Several input image data structures expressing wind vector change are considered and the prediction accuracy is compared between them. The performance of the proposed method is evaluated by the root-mean-square error and correlation coefficient between observed and predicted values.

1. Introduction

At present, electricity in Japan is mainly generated using fossil fuels, but fossil fuels are finite and emit CO_2, which causes global warming. For these reasons, renewable energy, which will never run out and does not emit CO_2 during power generation, has attracted attention in recent years. In particular, wind power generation, which can generate electricity as long as the wind blows, is being introduced worldwide [1]. However, wind power generation has large output fluctuations due to changes in wind speed. For this reason, power companies adjust the power supply and demand balance using thermal and pumped-storage power generation. In order to operate the power system efficiently and stably, it is important to predict the output of wind power generation.

In our previous research, A. P. Sari of our laboratory proposed a prediction model of wind speed and direction with a deep neural network using wind speed vector images as input [2]. The model combines convolutional long short-term memory (CLSTM) and convolutional neural network (CNN), which is effective for image analysis. The input is an image that expresses the wind speed and direction as a plot at 10-min intervals in one hour. Then, multiple prediction models are proposed and the prediction accuracy is compared. However, the input data structure was considered to be insufficient.

Therefore, we aim to improve the prediction accuracy of wind speed by optimizing the expression method of the input image. Several input image styles with different size and color of plots to well express the time sequence of wind change are considered. The accuracy of the prediction results is evaluated by comparison with observed wind data of several months.

2. Time Delay Problem of Wind Speed Prediction

The time delay problem of wind speed prediction, as shown in Fig. 1, has been studied. The time delay is a major issue of wind speed prediction based on observed data. Anggi et al. proposed a wind speed and direction prediction model by using deep learning with CLSTM and CNN layers. Then, the input images indicate observed wind speed and direction at 10-min intervals in one hour as plots on 2D coordinates to express not only the wind vector but also the time sequence of wind change. However, the prediction accuracy was not sufficiently improved in terms of the delay. In this work, several input image expressions of wind change are considered with different sizes and color plots.

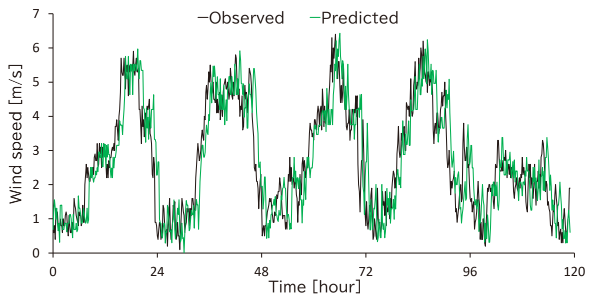


Figure 1: Examples of forecast result for June 2–6, 2018[2]

3. Input Image Dataset

3.1 Expression of wind on two-dimensional plane

The wind speed and direction obtained from AMeDAS are observed at 10-min intervals. The wind direction is represented by 16 azimuths, as in Fig. 2. Then the wind vector is represented in a two-dimensional coordinate system, as shown in Fig. 3(a). Also, the wind information can be represented by $v_X(t)$ and $v_Y(t)$, as shown in Fig. 3(b), and the X-axis and Y-axis mean the wind speed components of the east–west and north–south directions. From Fig. 3(a), the wind vector components $v_X(t)$ and $v_Y(t)$ are calculated as

$$v_X(t) = v(t) \cdot \cos\varphi(t) \quad (1)$$

$$v_Y(t) = v(t) \cdot \sin\varphi(t) \quad (2)$$

where $v(t)$ is the wind speed [m/s] and $\varphi(t)$ is the wind direction [°].

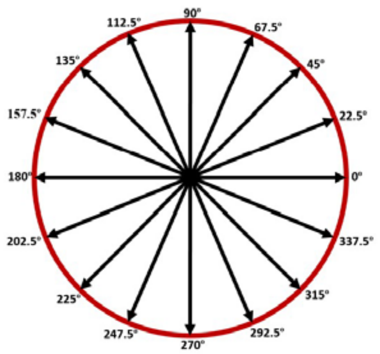
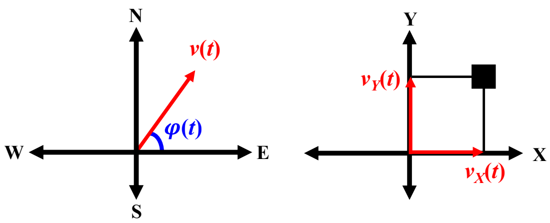


Figure 2: Representation of 16 directions of wind



(a) Wind vector diagram (b) Wind components of $v(t)$

Figure 3: Wind speed and direction on a 2D coordinate

3.2 Dataset structure

The wind vector is drawn on an image (128×128 pixels) at position $p = (p_X$ and $p_Y)$ calculated by

$$p_X(t) = 64 + \frac{64}{v_{max}} v_X(t) \quad (3)$$

$$p_Y(t) = 64 - \frac{64}{v_{max}} v_Y(t) \quad (4)$$

where 64 is half the image size and v_{max} is the maximum wind speed. In this work, v_{max} is set to 20 m/s which does not exceed the wind speed observed in Tokushima, Japan.

The wind vectors from $\boldsymbol{p}(t-5)$ to $\boldsymbol{p}(t)$ are drawn as shown in Fig. 4 with the oldest data in blue and the latest data in red. At this time, the change in color of the plotted points expresses the change over one hour. Then six images are composed into a image $m(t)$ to express the wind change. Also, in order to express the wind change pattern for one hour at 10-min intervals, nine images from $m(t-8)$ to $m(t)$ are made in the same way. Those nine images are input to the prediction model.

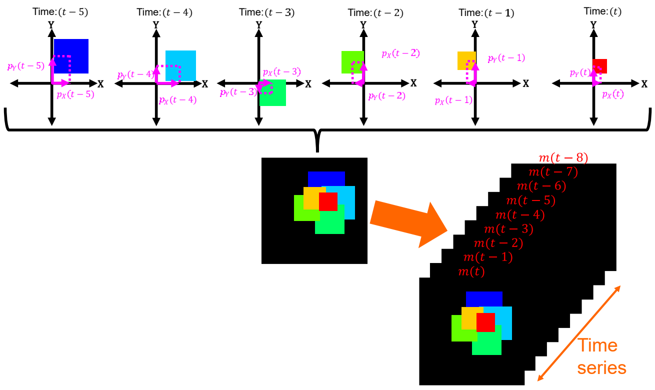


Figure 4: Input image construction process

4. Prediction Model of Wind Speed and Direction

The prediction model of wind speed and direction is shown in Fig. 5. The model is composed of an encoder network and a forecaster network with CLSTM and CNN. The nine images with the size of 128×128 pixels are input. The output is the wind vector one hour in the future to consider the adaptability of thermal power generation plant. Table 1 shows the learning parameters. In this paper, the same model configuration and learning parameters are used as those in our previous study [2]. The encoder network consists of three convolutional layers and five CLSTM layers, and the forecaster network consists of six CLSTM layers and three deconvolutional layers. The number of filters in the three convolutional layers is 16, 16, and 32, respectively, and the number of filters in the three deconvolutional layers is 32, 16, and 1, respectively. The stride width of the filters in the convolutional and deconvolutional layers is 2. The number of units in the CLSTM layer is 32. All kernel sizes are 5×5. The fore input sequence uses an array of zeros in the forecaster network. The internal state of the CLSTM layer of the encoder network is copied to the CLSTM layer of the forecaster network, and the outputs of all CLSTM layers of the forecaster network are concatenated as inputs to the last CLSTM layer and fed to the deconvolutional layer. One image with the size of 128×128 pixels is output from the last deconvolutional layer.

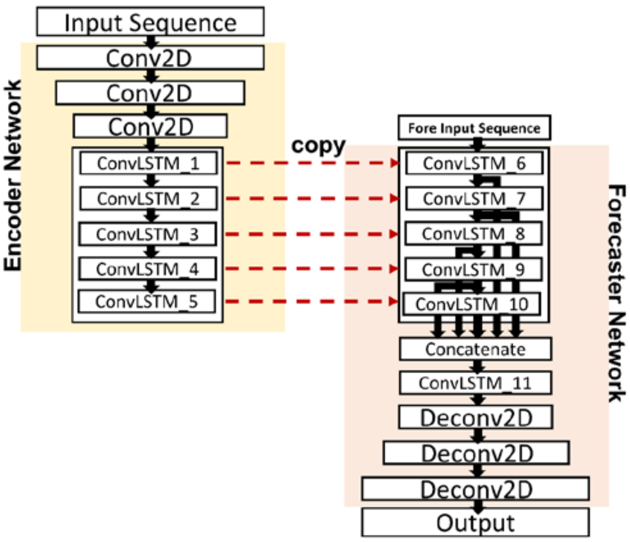


Figure 5: Structure of prediction model

Table 1: Learning parameters

Loss function	Mean square error (MSE)		
Activation Function	Leaky ReLU		
Optimizer	RMSProp	lr	0.001
		ρ	0.9
Batch size	4		
Epochs	20		

To obtain predicted wind speed and direction, the position of the center of gravity and the maximum coordinate ($\hat{p}_X(t)$, $\hat{p}_Y(t)$) is calculated from the output image represented by values from 0 to 255 in grayscale. Then ($\hat{p}_X(t)$, $\hat{p}_Y(t)$) is converted to $\hat{v}_X(t)$, $\hat{v}_Y(t)$ as

$$\hat{v}_X(t) = \frac{v_{max}}{64}(\hat{p}_X(t) - 64) \tag{5}$$

$$\hat{v}_Y(t) = \frac{v_{max}}{64}(64 - \hat{p}_Y(t)) \tag{6}$$

where v_{max} is the preset maximum wind speed, which is the same value used in Eqs. (3) and (4), and $\hat{v}_X(t)$, $\hat{v}_Y(t)$ are east–west and north–south components of predicted wind speed, respectively. The predicted wind speed is calculated from $\hat{v}_X(t)$ and $\hat{v}_Y(t)$ as

$$\hat{v}(t) = \sqrt{\hat{v}_X^2(t) + \hat{v}_Y^2(t)} \tag{7}$$

where $\hat{v}(t)$ is the predicted wind speed [m/s].

5. Prediction Results

5.1 Suitable square plot size

In this paper, we first examine the size of the square plot points in the input image to determine suitable plot size. Set all six plots to the same size, and increase the size from 2×2 pixels to 20×20 pixels by adding two pixels on each side. Figure 6 represents 10 types of input image.

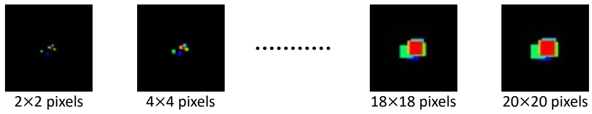


Figure 6: Examples of input images from 2×2 pixels to 20×20 pixels

The prediction error is evaluated as the following root mean square error (RMSE),

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}}\sum_{k=1}^{\mathrm{N}}(\hat{y}_k - y_k)^2} \tag{8}$$

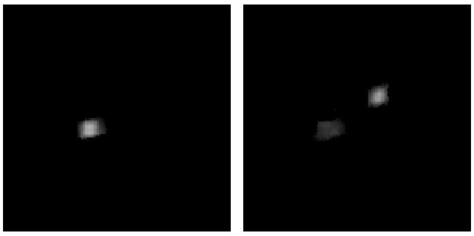
where N is the number of data, $\hat{y}_k$ is the predicted wind speed and y_k is the actual wind speed. In addition, the prediction accuracy is also evaluated by the correlation to evaluate time delay. The predicted image is output as shown in Fig. 7, and the wind prediction values are obtained using Eqs. (5) to (7). At this time, we evaluate the prediction accuracy by comparison. With the pixel coordinates extracted from the image using at the center of gravity value or the maximum value. Each prediction result is shown in Table 2.

Table 2: Prediction accuracy

Image size (pixel)	RMSE [m/s]		Correlation coefficient	
	Centroid	Maximum	Centroid	Maximum
2×2	2.20	1.17	0.728	0.807
4×4	2.31	1.18	0.694	0.810
6×6	2.21	1.21	0.715	0.814
8×8	2.14	1.36	0.732	0.827
10×10	2.37	1.40	0.701	0.819
12×12	2.16	1.24	0.689	0.824
14×14	2.27	1.48	0.746	0.806
16×16	2.52	1.77	0.708	0.790
18×18	2.50	1.86	0.657	0.747
20×20	2.46	1.94	0.725	0.727

Table 2 shows that when pixel values at the center of gravity are obtained, the RMSE value becomes larger when the plot size is larger, resulting in lower accuracy. The correlation coefficients did not change much at any plot size. Next, looking at the case where the maximum value is introduced, it can be seen that as the plot size increases, the RMSE value increases, and that the correlation coefficient is high when the plot size is neither too small nor too large. Moreover, the accuracy of prediction is higher when taking the maximum value rather than the center of gravity value. This is thought to be due to the fact that the predicted image is output with two main distributions. There are mainly two cases of predicted images, as shown in Fig. 7. If the coordinates of the center of gravity are taken, as in Fig. 7(b), it may not be possible to obtain the position in the coordinates with a higher probability of the predicted plot point.

Figure 8 shows the prediction results when the coordinates of the maximum value of 8×8 pixels, which had the strongest positive correlation, were obtained. From Fig. 8, it can be seen that the predicted value has a time delay during the rise period, but the time delay is relatively small during the fall period of wind speed. Also, it can be seen that 0 m/s is likely to be taken when the value of wind speed is small.



(a) case 1 (b) case 2

Figure 7: Predicted images

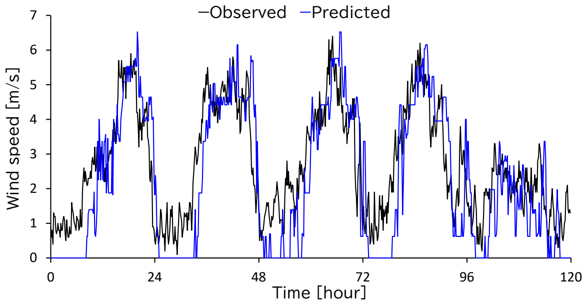


Figure 8: Predicted wind speed for June 2–6, 2018

5.2 Change six plot sizes on the wind vector image

By changing the size of the six plotted points, the degree of change from the past wind speed is expressed. Set the latest data to 8×8 pixels and increase by 2×2 pixels so that the oldest data is 18×18 pixels. This is called variable size. The coordinates of the predicted value is the maximum value. Table 3 shows the evaluation of prediction accuracy, and Fig. 9 shows the prediction results. The same size in Fig. 9 means that the size of all six plot points is 8×8 pixels. The conventional method refers to the method used in our previous research. The most recent data is plotted as the largest square, and the other five are plotted as smaller squares of the same size and connected by lines. From Table 3, it is confirmed that changing the plot size decreased the prediction error, but the correlation coefficient also decreased. In addition, as shown in Fig. 9, the existing method has the smallest time delay at startup. Regarding the time delay during the fall period, there is not much difference between the methods. By changing the plot size, it is confirmed that the wind speed change at low wind speed can be captured better. It was not possible to obtain prediction accuracy that surpasses that of the conventional methods.

Table 3: Wind speed prediction accuracy

	RMSE [m/s]	Correlation coefficient
Same size (8×8 pixels)	1.36	0.827
Variable size	1.31	0.785
Conventional method	1.01	0.865

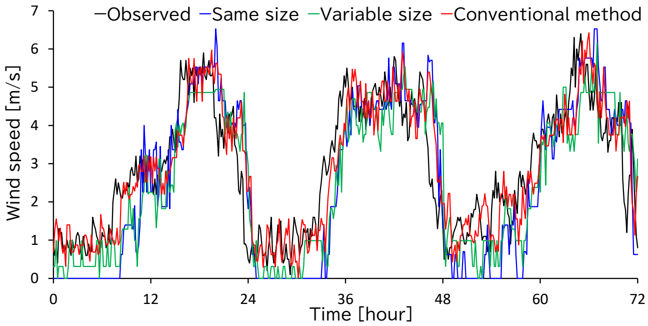


Figure 9: Predicted wind speed for June 2–4, 2018

6. Conclusions

In this study, we optimized the square plot size of the input image with the aim of improving the prediction accuracy. As a result, changing the six plot sizes made it easier to detect changes over time, but there was no significant difference in prediction accuracy. In addition, the time delay problem was not sufficiently resolved.

Future tasks are is to optimize the number of plot points, colors, and number of input images.

References

[1] Agency for Natural Resources and Energy: FY2018 Annual Report on Energy (Energy White Paper 2019), pp. 208-209, 2019.

[2] A. P. Sari: Study on forecasting of wind speed and direction using deep neural network, Doctoral Thesis in Tokushima University, 2021.