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Improving Wind Speed Forecasts Using Deep Neural Network

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Abstract

Wind speed data constitute important weather information for aircrafts flying at low altitudes, such as drones. Currently, the accuracy of low altitude wind predictions is much lower than that of high-altitude wind predictions. Deep neural networks are proposed in this study as a method to improve wind speed forecast information. Deep neural networks mimic the learning process of the interactions among neurons in the brain, and it is used in various fields, such as recognition of image, sound, and texts, image and natural language processing, and pattern recognition in time-series. In this study, the deep neural network model is constructed using the wind prediction values generated by the numerical model as an input to improve the wind speed forecasts. Using the ground wind speed forecast data collected at the Boseong Meteorological Observation Tower, wind speed forecast values obtained by the numerical model are compared with those obtained by the model proposed in this study for the verification of the validity and compatibility of the proposed model.

Keywords: *Wind speed, Deep learning neural network, Aviation weather, Weather forecast.*

1. INTRODUCTION

Recently, drones are used in various fields such as transportation, logistics, rescue activities, telecommunications, aerial photography, control, and surveillance, and their application fields are expanding even further. To speed up delivery and reduce shipping costs, logistics companies such as Amazon, UPS, and DHL are developing drones for delivery services. Furthermore, EHang, a Chinese drone company, is currently developing and commercializing drones for transporting people to avoid road traffic jams using the air taxi called 'EHang 184.'

Accurately predicting the weather conditions is crucial for the safe operation of drones. Most drones use electric motors rather than the engines found in conventional manned aircraft. Consequently, they are vulnerable to water because they are built with electronic components and are difficult to control in the presence of strong winds. These environmental factors associated with the weather are vital for the operation of manned aircrafts. Generally, weather factors such as visibility, icing, thunderstorm, wind shear, microburst, and turbulence are crucial factors for safe flight operation[1][2]. For the safety of flight operations, airports currently provide aviation service workers with meteorological aerodrome reports (METAR) every hour and terminal aerodrome forecasts (TAF) every 6 h [2]. However, the existing aviation weather forecasts data are

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for high-altitude aircraft and may have different characteristics from low-altitude forecasts, which are directly influenced by the terrain and building structures. As the use of drones in various fields and the demand for long-distance flights using drones continuously increase, more accurate wind speed forecasts for low-altitudes are necessary for the safe operation of flights, such as drones flying at low-altitudes.

This study was conducted to predict the low-altitude wind speed for the safe operation of low-altitude flights. The rest of this paper is organized as follows. In Chapter 2, deep neural networks, which are used to predict low-altitude winds, are introduced. Subsequently, in Chapter 3, the proposed deep neural network model is implemented. In Chapter 4, the wind speed prediction values from the proposed model are compared with the actual wind speed measurements, and in Chapter 5, conclusion is resented based on the proposed wind speed prediction model.

2. DEEP NEURAL NETWORK MODEL

The development of artificial neural networks started with the perceptron learning model, which mimics the learning process of the interactions among neurons in the brain, and this model was developed in 1958 by Rosenblatt. There have been advancements in various forms ever since [3]. Neural networks in the early days could only be applied to a limited number of problems of linear separation with a single layer neural network. Although various attempts have been made to construct deep neural network models with a multi-layer structure to solve more complex problems, issues such as overfitting and disappearance of gradients have risen. These problems of deep neural networks have been improved by the error backpropagation algorithm and using nonlinear functions proposed by P. Werbos in 1975, and by the optimal initialization of neural network weights proposed by G. Hinton in 2006 [3]-[5].

In general, a deep neural network consists of an input and output layer and hidden layers, where more than two hidden layers are present. Figure 1 shows the structure of a deep neural network having n number of hidden layers. The circles in the figure represent the nodes of the hidden layer, and each node contains values of the weighted sum of its inputs and activation functions. The connecting lines of each node represent the signal flow and get multiplied by the weight values. The weights are updated through the learning process of minimizing the cost function, where the difference between the output values obtained through the model and the actual desired values are minimized [6].

3. DEEP NEURAL NETWORK MODEL FOR WIND SPEED PREDICTION

3.1 Wind Speed Predictions and Measurements

The average wind speed measured for 10 min at an observation point was used as the wind speed in this study, and weather research and forecasting (WRF) model was used for the wind information prediction model. The WRF is a fully compressible non-hydrostatic model which uses Arakawa-C grid for the horizontal grid and hydrostatic

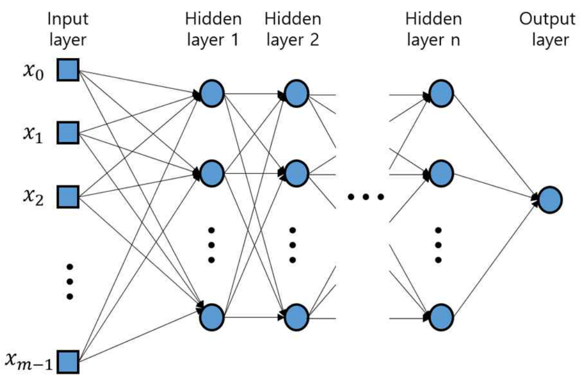

Figure 1. Deep neural network's structure

barometric vertical based on the terrain, for the vertical grid [7]. The WRF is a medium-scale numerical weather prediction model that can generate various weather information for the areas required for the study by configuring the model-driven environment. It can also generate low-altitude level weather information of 150 m or less, which is required for this study. To predict the low-altitude wind speeds, a domain was set at the height of 500 m, and precise predictions were performed on the target areas where the actual low altitude level observations were possible. In this study, wind speed values predicted using the WRF were used as the input values.

Figure 2. Boseong Meteorological Observation Tower

The actual wind speed measurement data used in this study is from the data collected by the Boseong Meteorological Observation Tower shown in Figure 2. The meteorological observation tower, a facility that can measure low altitude level data, measures the wind speed data in 11 different levels from altitudes of 10–300 m.

In this study, the wind speed forecast data using the WRT model in Boseong, Jeollanam-do, and the actual wind speed collected at the Boseong observatory from January to June of 2018 are used as the input values and measured values for the wind speed prediction model. For each data generation period, the forecast data using the WRT model are generated with 14 different parameters such as forecast date, forecast time, temperature, humidity, atmospheric pressure, precipitation, wind speed, air condition variables, and out of these, only the wind speed of the forecast data was used. The forecasts are generated twice per day, and the forecast data at each instance were generated from the beginning reference time to +72 h. For the training process, the error values among the data measured by the Boseong observatory were removed prior to the training.

3.2 Wind Speed Forecast Model Implementation

To construct a wind speed forecast model, the configurations were set as shown in Figure 3. The values of each node and layer were selected empirically by changing the number of nodes and layers through trial-and-error.

The input nodes were set as 53 nodes to use the data from 0 to 52 h out of 73 forecast data (wind speed data from hour 0 to hour +72) from the WRT. Since the wind speed forecast data are from hour 0 to hour +72, there could be a big difference in the actual measured wind speed. To solve this, the number of nodes and layers in the hidden layers were increased to reflect the actual measured values more accurately. As shown in Figure 3, seven hidden layers were constructed with 200 nodes in hidden layer 1, 400 nodes in hidden layer 2, 800 nodes in hidden layer 3, 1,000 nodes in hidden layer 4, 800 nodes in hidden layer 5, 400 nodes in hidden layer 6, and 200 nodes in hidden layer 7 based on the empirical evidence. Since the WRT model requires approximately 6 h to calculate the forecast, the output nodes were set as 48 nodes to make predictions from hour 6 to hour 53 for the comparison of the forecast and actual measured values.

For the learning process, the wind speed forecast values, which are used as input values, were normalized to lie between -1 and 1. The activation function used tanh to construct a regression model of the normalized wind speed forecast values between -1 and 1. Subsequently, the root mean square error (RMSE) was used as the objective function, and the Adam optimizer was used to optimize the function. To prevent overfitting of the trained data, 10% of the results from the activation function of each layer were dropped out. For the initial value of the weight, the method that reflects a uniform distribution in the Xavier initialization, which shows effective results when activation functions are nonlinear (ex. sigmoid, tanh), was used.

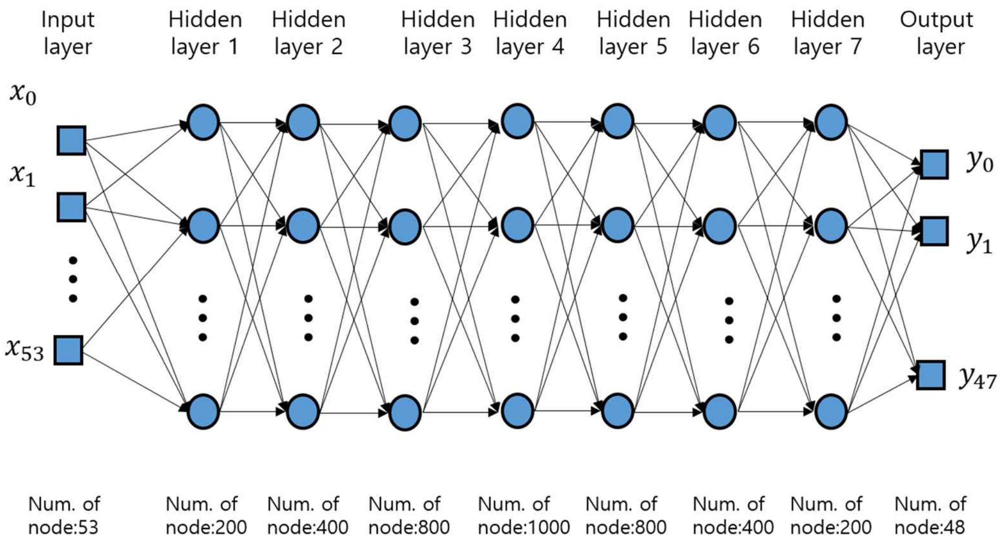

Figure 3. Wind speed forecast model

4. SIMULATION

In this study, ground wind speed data collected from Boseong Meteorological Observation Tower during the period from January to June of 2018 were used. Seventy percent (222 datasets) of the total data were used as training data, while 15% (47 datasets) were used for validation, and the rest 15% (48 datasets) were used as test data for simulation. The learning rate was set to 0.001, and the epoch value was set as 200 for the simulation. Figure 4 shows the results on the loss of train and validation. A suitable learning process was conducted with the loss of train being 0.05 and validation of 0.04.

The wind speed prediction model developed through the training process was verified using the test data (48 datasets). In Figure 5, the RMSE value of the predicted wind speed values from the numerical model and the actual measured values, and the RMSE value of the predicted wind speed values from the deep neural network model and the actual measured values, are shown for each measurement time. The RMSE values for each measurement time are values based on the predicted wind speeds and the actual measured wind speeds from hour +6 to hour +53. Although the RMSE values of the numerical model are shown to be lower for some parts, generally, RMSE values of deep neural network models are lower than those of numerical models. As shown in Figure 5, the RMSE of the numerical model was 0.0023, and the RMSE of the deep neural network model was 0.0012. The wind speed forecast model using the deep neural network model was similar to the actual measured wind speed better than the forecast model using the numerical model. Figure 6 shows the wind speed values for (a) tick=0, (b) tick=10, (c) tick=20, and (d) tick= 30 respectively. In each figure, blue represents the actual measured value, orange represents the deep neural network prediction values, and green represents the numerical model prediction values. Overall, the wind speed predictions generated through the deep neural network model correlated better with the actual measured wind speeds than the predictions generated by the numerical model.

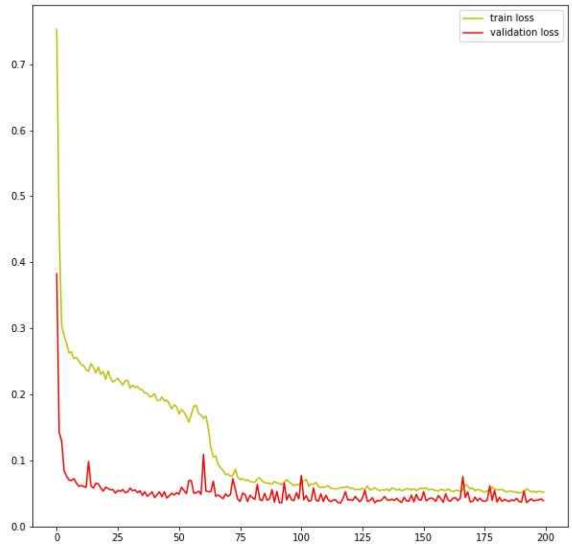

Figure 4. Result on the loss of train and validation

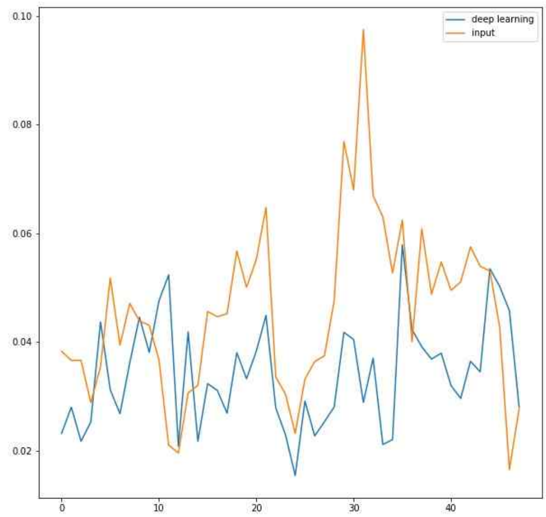

Figure 5. RMSE comparison between Wind Speed Prediction of Numerical Model and Deep Neural Network Model Using Test Datasets

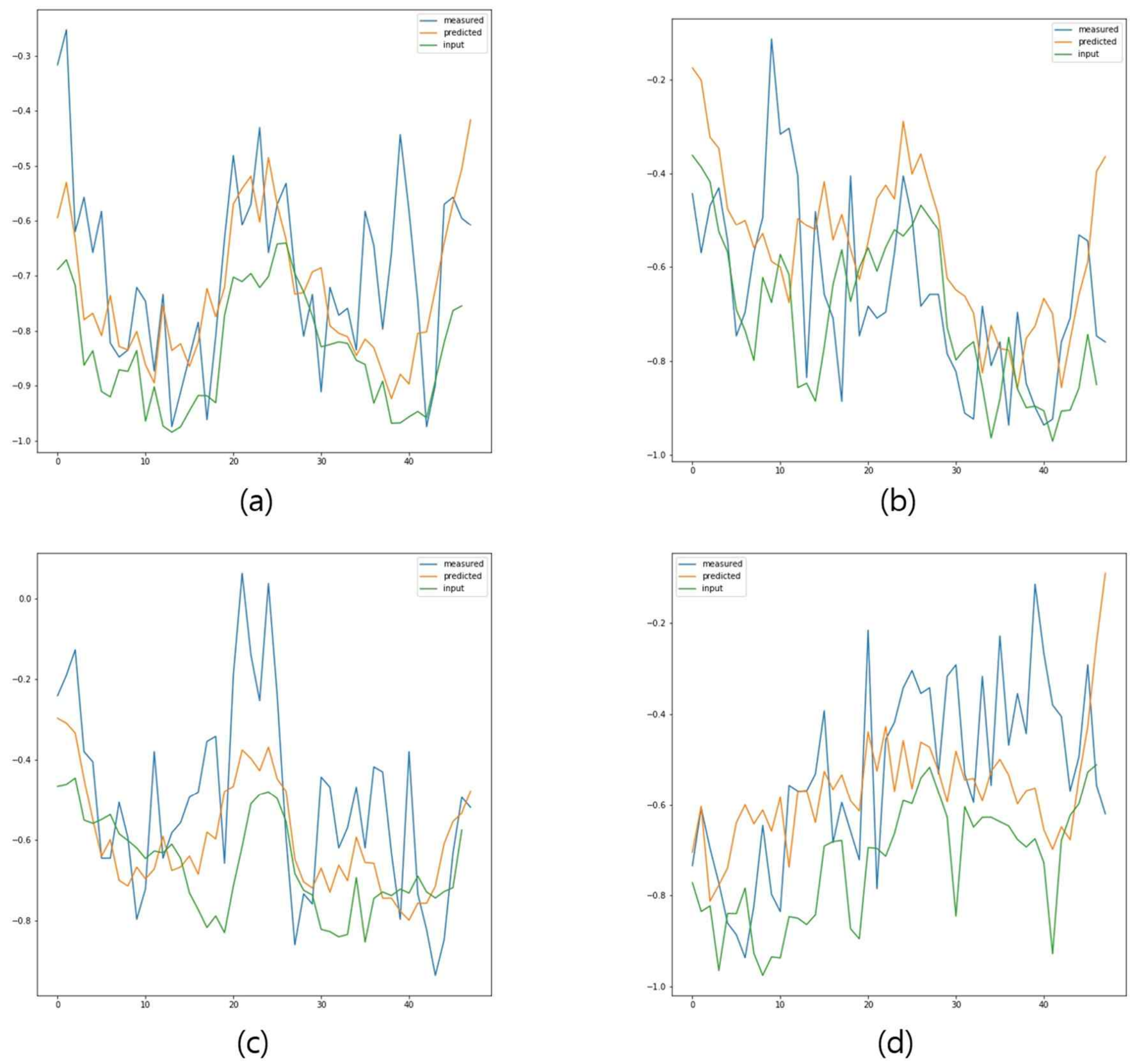

Figure 6. **Wind speed value of different ticks shown in Figure 5 on the test dataset: (a) tick = 0, (b) tick = 10, (c) tick = 20, (d) tick = 30. Blue displays the actual measured values, orange represents deep neural network prediction values, and green represents numerical model prediction values in the graphs.**

5. CONCLUSION

In this study, a wind speed forecasting methodology, which improves the forecasts derived from the meteorological numerical model for low-altitude aircraft, such as drones, was proposed. Typically, numerical meteorological models can predict near future weather forecasts relatively accurately; however, several errors occur when predicting weather forecasts of the distant future. To address this, an improved wind speed prediction model using a deep neural network was proposed in this study.

The proposed model featured seven hidden layers, with each layer having a 10% dropout to prevent overfitting. Tanh was used as the activation function, and the Xavier initialization, which is frequently used for nonlinear function weight initialization, was used for initializing values. The input and measured values were normalized to lie between -1 and 1.

To verify the validity and compatibility of the proposed model, the prediction values of numerical model of wind speed data from January to June of 2018 in Boseong were used as input values and the wind speed values measured from the ground by the Boseong Meteorological Observation Tower were used as the measured values to verify the suitability of the proposed model. The RMSE value of the predicted values and the actual measured value through the numerical weather prediction model was 0.0023, and the RMSE value of the predicted value and the actual measured value through the deep neural network model was 0.0012, which showed a twofold improvement in the performance.

As shown in Figure 6, the predicted values from the proposed model were relatively better than those from the numerical model; however, these estimated values were unsatisfactory in several areas. Currently, only the wind speed information was used to conduct wind speed forecast, and further research using other weather information related to wind speeds should be conducted to improve the accuracy of wind speed forecast.

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