Short-Term Wind Forecasting with Weather Data using Deep Learning - Case Study in Baron Techno Park

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Short-Term Wind Forecasting with Weather Data using Deep Learning - Case Study in Baron Techno Park

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Abstract: In a microgrid with small-scale renewable sources, the unpredictable and highly variable nature of wind necessitates the adoption of reliable wind forecasting technologies. This study employs artificial neural networks (ANNs), specifically the Long Short-Term Memory (LSTM) and Multi-Layer Perceptron (MLP), which are classified as Deep Learning (DL) networks. These models integrate diverse weather data, such as wind speed, temperature, humidity, and atmospheric pressure, derived from actual measurements collected in Baron Techno Park, an isolated microgrid situated in the coastal region of Yogyakarta, Indonesia. For various scenarios, the root-mean-square error (RMSE) and mean absolute error (MAE) performances of the proposed ANN-based multivariable model are given and contrasted. Furthermore, it examines the impact of incorporating multiple local variables in contrast to solely relying on wind power, comparing against the persistence method. The findings reveal that the model incorporating a comprehensive set of weather data as inputs attains the lowest RMSE and MAE values. It is also can be concluded that additional weather data, even though they show almost no correlation to wind power in Baron Techno Park can improve short-term wind power prediction, with an improvement of 2.3% for every addition of weather parameter.

Keywords: wind forecasting, coastal area, weather data, deep learning, ANN, microgrid, remote area

1. Introduction

According to the National Electricity General Plan or RUKN, Indonesia has established goals for its energy mix, including a proportion of Renewable Energy Technologies (RET) of 23% by 2025 and 31% by 2050, a reduction of greenhouse gas emissions of 29-41% by 2030, and a goal of net-zero emissions by 2060. Following those, numerous research on estimating national potential renewable energy have been conducted, such as hydro potential energy[1)], wind potential energy[2)], solar radiation[3)], Geothermal[4)], and a web-based tool for estimating a rooftop solar PV system's capacity to produce energy[5)].

Wind power is growing very rapidly all over the world and promising potential renewable energy to achieve Indonesia's target. The Ministry of Mineral and Energy Resources (MMER) of Indonesia states that wind power can deliver up to 154.88 GW once fully developed in line with its potential, consisting of an onshore potential of 60.65 GW and offshore potential of 94.2 GW. According to [6)], onshore locations along the south coasts of Java, South Sulawesi, Maluku, and NTT have high wind energy potential, with wind speeds of 6 to 8 m/s, power densities of 400 to 500 W/m2, and Annual Energy Production (AEP) of 4-5 GWh/year.

In addition to site selection[7,8)] and appropriate wind turbine design[9–11)], wind speed forecasting has a substantial impact on energy development and attaining the best results. On the other hand, wind energy's intermittent nature is one of the biggest drawbacks, which may lead to power instability and large fluctuations[12,13)]. Network operators must overcome the difficulties posed by fluctuating wind conditions to schedule spare capacity, stability, planning, and the dependability of the power system[14)]. Accurate wind forecasting is an effective technique for preserving the security of the electricity grid[15)].

Recent studies have created several techniques and models to increase the precision of wind speed forecastings, such as statistical models and Artificial Intelligence (AI) models. Statistical models are data-driven models that produce forecasts using past wind speed data. Among the many methods that have been researched and assessed, grey models[16], Markov Chain[17], exponential smoothing[18], ARMA[19], and ARIMA[20] models appear to be the most effective. Models for machine learning and artificial intelligence (AI/ML) are also data-driven models. In contrast to statistical models, AI approaches are better equipped to handle the nonlinearity of wind speed.. Some of the methods investigated within machine learning models include Support Vector Machine (SVM)[21], Decision Trees (DT)[22], Gaussian Process Regression (GPR)[23], and Extreme Learning Machine (ELM)[24], and Artificial Neural Networks (ANN)[25]

ANN has strong fault tolerance, real-time operation, self-learning, flexibility, and implementation ease. These structures, based on biological neurons, effectively address issues that cannot be defined analytically. One key advantage of ANN is its ability to generalize, accurately predicting data from unseen fractions of a dataset, even with noisy information[26]. Numerous studies propose ANN-based wind speed prediction models, highlighting their accuracy in complex topography[27]. ANNs have proven effective in situations involving complicated or poorly understood processes[28][29].

Deep Learning (DL), based on ANN techniques, has gained popularity for time series forecasting[30], especially in wind speed prediction. DL models, particularly deep neural networks, outperform other models in feature extraction, enhancing prediction accuracy. Various studies demonstrate the superiority of DL methods, including machine learning and deep learning, in predicting wind power and forecasting accuracy[31,32]. Novel approaches utilizing hybrid structures and advanced techniques like feature decomposition, self-attention, and optimization show improved results[33] [34] [35].

Although multiple approaches to wind speed prediction exist[36], achieving generalized and high-precision forecasts remains a challenge. Some models only improve results for specific forecast horizons and lack generalization. This paper proposes an accurate wind speed and wind power prediction model based on DL, utilizing multiple local meteorological measurements in Baron Technopark, Daerah Istimewa Yogyakarta Province. The primary objective is to enhance prediction accuracy while assessing the impact of using additional local variables compared to the persistence method.

Wind power estimation can be an essential tool for determining wind potential in a site, particularly if the location is planned to be utilized for constructing wind plants, especially one with a small capacity. Furthermore, this study is able to be applied to assess the performance of renewable energy plants[37] in order to identify improvements and plans for site expansion.

The rest of this paper is organized as follows. Section 2 describes the data and study area. Section 3 provides the methodology used in this paper, consisting of the network structure, dataset structure, and evaluation method. Section 4 provides results followed by a discussion about model performance. Section 5 concludes with a summary of the findings.

2. Dataset and Study Area

The study area is the Baron Technopark, which is in Planjan Village, Saptosari District, Gunung Kidul Regency, and Daerah Istimewa Yogyakarta Province. The Baron Technopark was founded in 2009 with a grant from NORAD-Norway, in the Parang Racuk Beach area, or west of Baron Beach. This location was built to support the National Energy Policy which targets the utilization of 23% NRE for electricity by 2025. The map presentation of the study area is shown in Fig. 1. Fig. 1 (a) shows the Baron Technopark location, and (b) shows the exact location of the weather sensor (blue) and the wind turbine (yellow). The distance between them is 100 m.

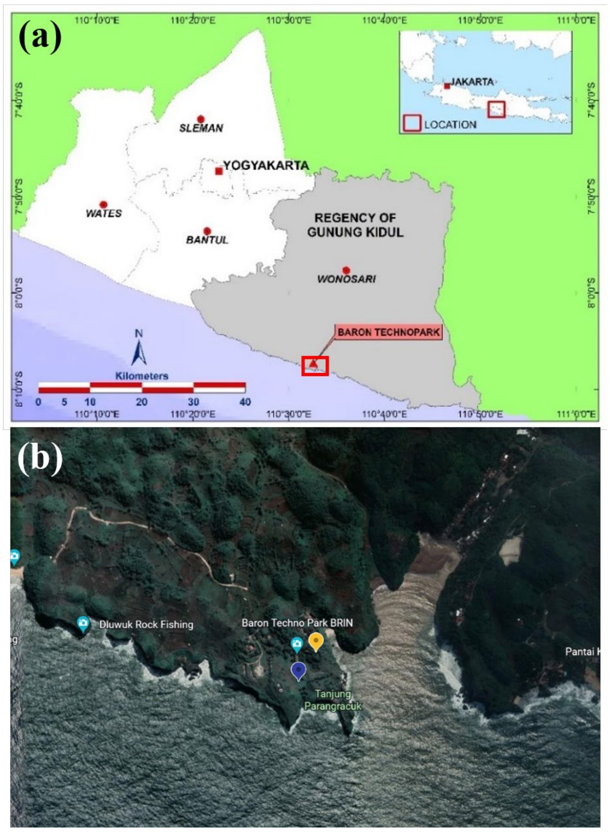

Fig. 1: (a) Baron Technopark Location, and (b) Exact location of weather sensor (blue) and a 5 kW wind turbine (yellow)

The electricity system in Baron Technopark consists of an off-grid microgrid supplied by a 36 kW capacity solar PV system, a 5 kW wind power generation, a hybrid inverter with a capacity of 25 kW, and a battery with a total capacity of 20 kWh. The wind turbine used in the Baron Techno Park Microgrid area is Fortis Wind 5 kW with DC power output. The control system is housed in the main control room and connected to a 25 kW hybrid inverter.

However, the wind turbine stopped operating in 2019 due to turbine malfunctions. This study serves as the preliminary study of future short-term wind forecasting for the microgrid's operational planning, as the wind turbine is planned to be re-installed in the near future. The weather data used in the study are from the year 2018, with h ground altitude of 20 m above sea level. The weather sensor is placed on a mast with a height of 30 m above ground. The weather data consist of wind speed, ambient temperature, ambient humidity, and atmospheric pressure. The DC power output of the wind turbine is also from the year 2018 with the same interval of 15 minutes. These data are then fed to the artificial neural network (ANN) learning process. Fig. 2 shows the scatter matrix of the data, showing the integrity and validity of the data. We can clearly see the positive correlation between wind speed and wind power. A negative correlation is also shown between ambient temperature and ambient humidity.

3. Methodology

3.1 Deep Learning (DL) Network Structure

Deep Learning (DL) techniques are based on Artificial Neural Networks (ANN) techniques. While the ANN networks are made up of three interconnected layers: input, hidden, and output layers, with only one hidden layer, DL networks incorporate more hidden layers, which determine the depth of the network. The following are 3 types of DL networks that are most relevant to time series forecasting[30)]:

1. Fully connected neural networks, the Multi-Layer Perceptron (MLP).
   The neurons in this feed-forward ANN are entirely linked, making it the simplest form.. Recurrent neural networks (RNN).
2. Recurrent neural networks (RNN) were developed to handle time-dependent data. While RNNs have natural support for sequence data, MLPs ignore the temporal associations in the input data since each time step in an RNN is connected to the one before it, simulating the data's temporal dependency [37,38)].
3. Convolutional networks (CNN)
   CNNs are DL networks that were originally used for computer vision. Several classification tasks, including object identification, speech recognition, and pattern recognition, are regarded as state-of-the-art.

Lopez[42)] suggests LSTM's reliability in generating wind power forecasts using historical and NWP data. Shi et al[43)]. find that recursive and direct variational model decomposition LSTM networks outperform traditional neural networks for wind power prediction. Vinothkumar et al[44)]. discover that the recurrent LSTM model performs better than other models.

For short-term predictions, MLP integrated into hybrid models provides steady and consistent wind forecasts[45,46]. Iqdour et al.[47)] demonstrate the successful use of MLP neural networks for wind speed prediction. MLP also accurately predicts wind speed at various heights in

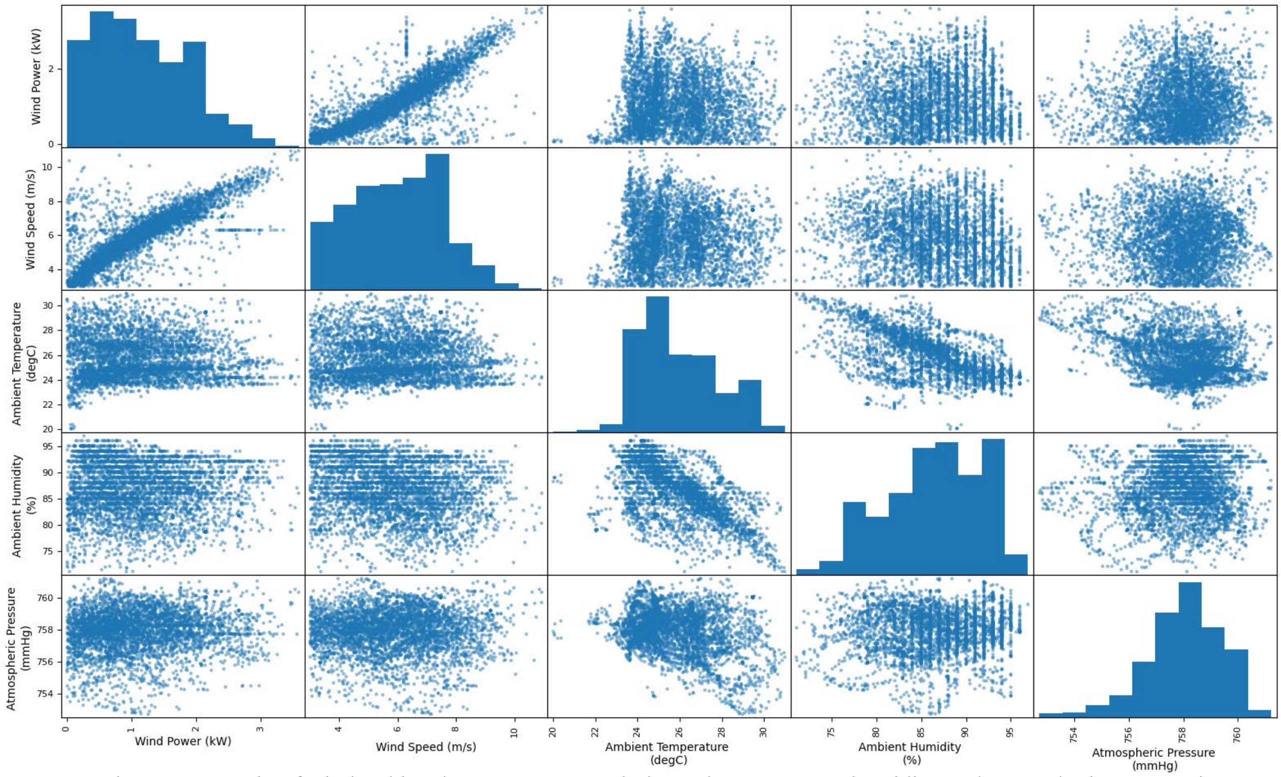

Fig. 2: The scatter matrix of wind turbine dc power output, wind speed, temperature, humidity, and atmospheric pressure in Baron Technopark

Uruguay[48] and Zaragoza[49].

All of the preceding research shows that DL algorithms, particularly LSTM and MLP, can predict wind energy projections reliably and precisely. However, making an exact prediction remains challenging, and a universal model is not possible. As a result, each situation necessitates a local dataset of wind speed, weather data, and location. Each model must be specific, developed, and trained.

We incorporate 3 types of DL networks; namely LSTM, MLP, and a hybrid of LSTM and MLP. Given the stochastic nature of the evaluation procedure and the differences in numerical precision, comparing 3 different types of DL networks would give a certain confidence level about the impact of the weather parameters to the forecasting result. We also run the each of training process 5 times and average the results.

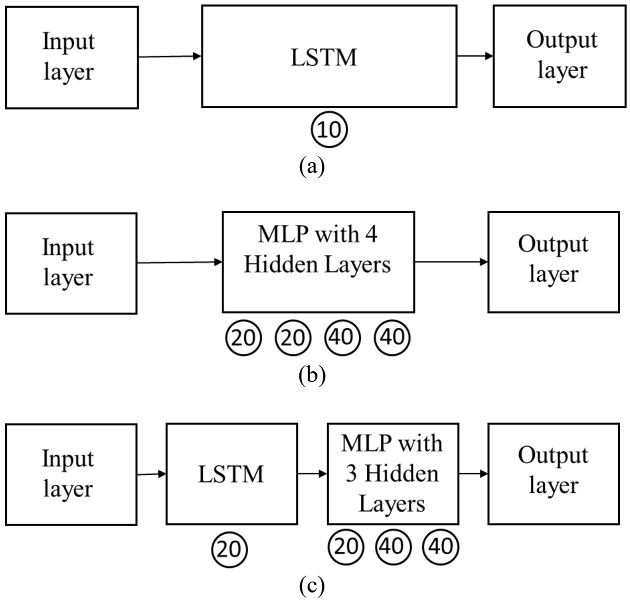

Fig. 3: DL Network Structure used in this paper, (a) LSTM, (b) MLP, (c) Hybrid of LSTM and MLP

Structure (a) consist of one input layer, one output layer, and 1 hidden layer of LSTM with 10 nodes. Structure (b) consist of the same input and output layer but with 4 hidden layers of MLP, with the following number of nodes: 20,20,40,and 40. Structure (c) has the same input and output layer but with 1 hidden layer of LSTM consists of 20 nodes and 3 hidden layers of MLP.consist of 20,40,and 40 nodes. The programming is done using python.

3.2 Dataset Structure

The forecast objective is to perform a D-1 24-hour prediction using data from the last 6 days. In this supervised training approach, all of the DL architectures require training inputs and outputs. We employed the most relevant meteorological parameters as wind power forecast input data in accordance with Nikolaidis's research[50]. The power output of a wind turbine is determined by factors such as wind speed, the size of the rotor blades, and air density. Air density, which represents the mass per unit volume of the Earth's atmosphere, is particularly important in estimating wind power for aggregated generation plants at a specific height. Similar to atmospheric pressure, air density decreases as altitude increases. It can also vary due to fluctuations in temperature or relative humidity. Unlike wind speed or air density, wind direction does not directly impact the power output of a turbine.

The dataset structure used for training inputs and outputs is as follows. Let **X** be the dataset input and **y** be the dataset output. X is organized as a two-dimensional array consisting of each weather data according to the combination used, removing the last day of data (to be predicted). There are 5 dataset combinations; combination 1 only uses wind power as input, combination 2 uses wind power and wind speed, combination 3 uses wind power, wind speed, ambient humidity, and so on. The input data structure is shown in Fig. 4.

The output structure **y** consists of the Wind Power (x_1) after six days following the input. Fig. 5 shows the input-output pair. The input and output are then split into training and testing datasets, with the ratio of samples of 80:20.

$$\mathbf{X} = \begin{bmatrix} X(t) \\ X(t+1) \\ X(t+2) \\ X(t+3) \\ X(t+4) \\ X(t+5) \end{bmatrix} = \begin{array}{c} \begin{array}{ccccc} \text{Wind Power} & \text{Wind Speed} & \text{Ambient Humidity} & \text{Ambient Temperature} & \text{Atmospheric Pressure} \end{array} \\ \begin{bmatrix} x_1(t) & x_2(t) & x_3(t) & x_4(t) & x_5(t) \\ x_1(t+1) & x_2(t+1) & x_3(t+1) & x_4(t+1) & x_5(t+1) \\ x_1(t+2) & x_2(t+2) & x_3(t+2) & x_4(t+2) & x_5(t+2) \\ x_1(t+2) & x_2(t+2) & x_3(t+2) & x_4(t+2) & x_5(t+2) \\ x_1(t+2) & x_2(t+2) & x_3(t+2) & x_4(t+2) & x_5(t+2) \\ x_1(t+5) & x_2(t+5) & x_3(t+5) & x_4(t+5) & x_5(t+5) \end{bmatrix} \end{array}$$

Fig. 4: Input data structure

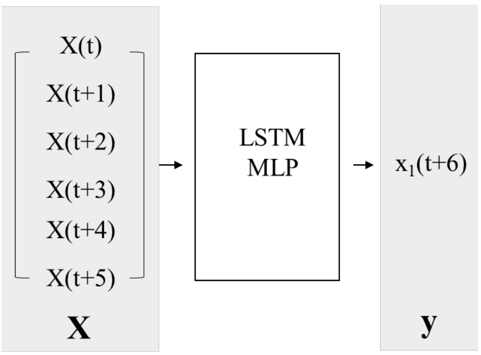

Fig. 5: Input-output pair

3.3 Evaluation Method

This paper applies statistical metrics as a method in the outcome between the result prediction and the actual value. The methods are RMSE and MAE. The Root Mean Square Error (RMSE) is a method of evaluating metrics that uses a standard deviation from a prediction of errors or residuals[51)]. Residual is the difference between the predicted value and the actual value. The formula for RMSE is shown in equation (1).

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

$\hat{y}_i$: actual value N: number of observations
y_i: predicted value i : increment

The second metric is the Mean Absolute Error (MAE). The MAE calculates the average magnitude of the errors between the predicted and the actual value without considering their direction. The formula for MAE is shown in equation (2).

$$MAE = \frac{1}{N}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (2)$$

$\hat{y}_i$: actual value N: number of observations
y_i: predicted value i : increment

4. Result and Discussion

Due to data integration and availability, the wind power data are only available for 6 months from July 2018 to December 2018. Hence, we pre-processed the other weather data to fit the same DateTime range.

The evaluation of wind power forecast using different dataset combinations is as follows. The training iteration for each combination is 35 iterations. The learning rate is 0.001. Combination 1's input is only wind power (x_1), Combination 2's input is wind power and wind speed (x_1 and x_2), Combination 3's input is wind power, wind speed, and humidity (x_1, x_2, and x_3), Combination 4's input is wind power, wind speed, humidity, and temperature (x_1, x_2, x_3, and x_4), and Combination 5's input is wind power, wind speed, humidity, temperature, and atmospheric pressure (x_1, x_2, x_3, x_4 and x_5).

The evaluation of these combinations using LSTM, MLP, and LSTM-MLP are shown in Table 1. Color gradients are used to highlight the decrease in error between combinations and DL type used, with darker color showing lower error. Gradient of greens for RMSE, and gradient of browns for MAE.

The results show that both the RMSE and MAE are reduced further with additional weather data as inputs. This is also seen in each type of DL used. Combination 5 has the lowest MAE and RMSE, indicating that it has the highest accuracy and stability among these combinations.

Table 1. The evaluation of wind power forecast using different dataset combination and different DL architectures

	Com. 1	**Com. 2**	**Com. 3**	**Com. 4**	**Com. 5**
Data used as inputs	x1	x1, x2	x1, x2, x3	x1, x2, x3, x4	x1, x2, x3, x4, x5
			LSTM		
RMSE	0.8286	0.8076	0.7842	0.7725	0.7662
MAE	0.6517	0.6413	0.6162	0.606	0.6043
			MLP		
RMSE	0.9498	0.9100	0.8919	0.8859	0.8796
MAE	0.786	0.7385	0.7219	0.7223	0.7031
			LSTM-MLP		
RMSE	0.656	0.6472	0.6213	0.61345	0.6043
MAE	0.4594	0.4502	0.4427	0.4281	0.3875

Moreover, eventhough these results show that the LSTM-MLP yield the lowest errors, the hyper-parameters used are different so it cannot be concluded that this DL type is better. However, LSTM is clearly superior than MLP because with less number of hyper parameters (nodes and layers), it consistently yield better results than MLP.

The wind power forecast results visualization of different DL type, comparing Combination 1 and Combination 5 are presented in Fig. 6. Combination 1, used in both (a), (c), and (e), shows the training prediction (green) fail to predict the higher values of the actual wind power (blue). Combination 5, used in (b), (d), and (f), shows closer predictions with actual value specifically on higher values of actual wind power data. Meanwhile, in the testing phase (red line), Combination 1 in all DL type has comparable flow and form to the actual, but the value gap is greater than Combination 5. It is also apparent that LSTM-MLP successfully predicts lower values, as opposes to MLP and LSTM.

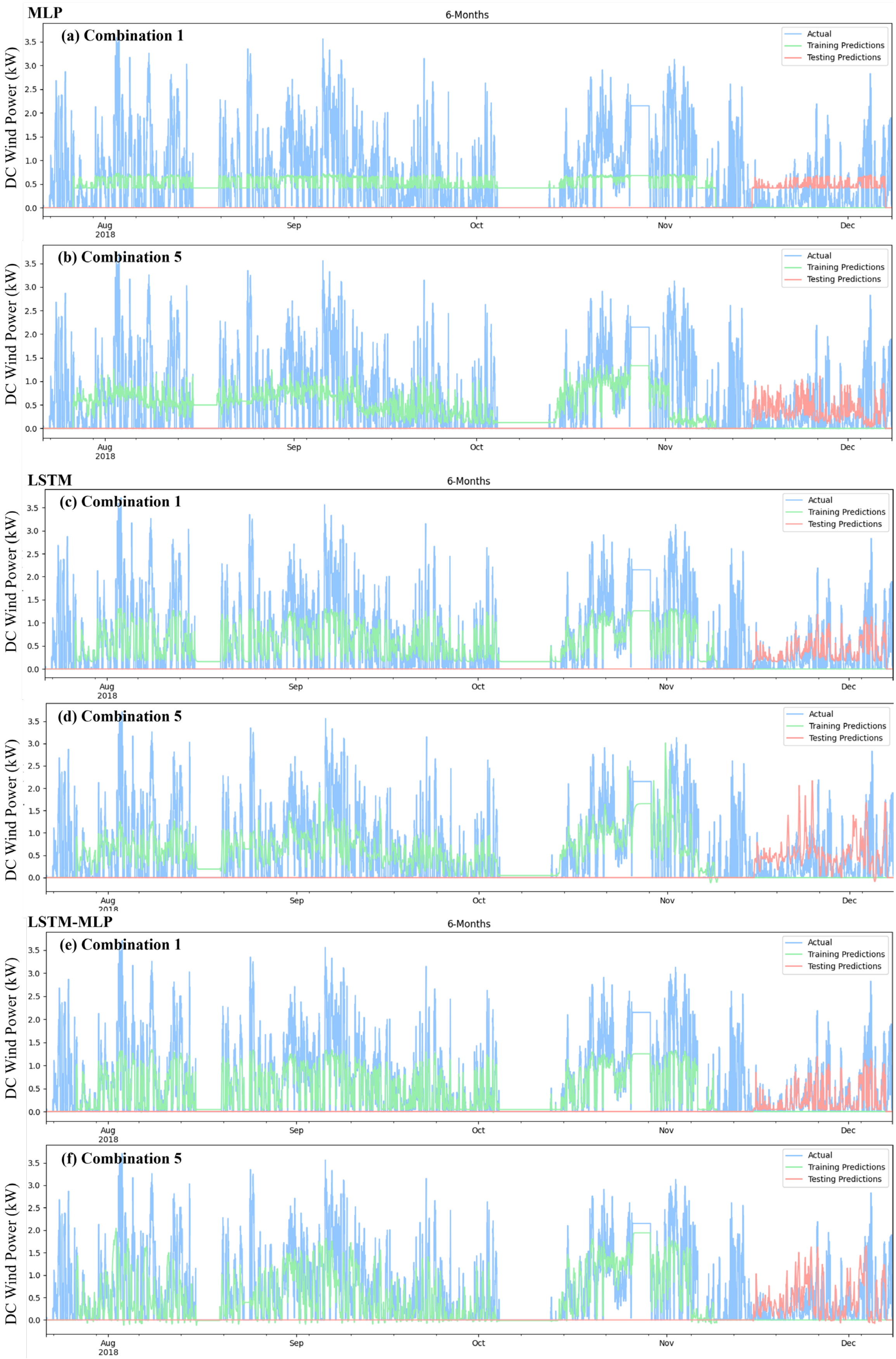

Fig. 6: Wind power forecast result of MLP, LSTM and LSTM-MLP architectures, comparing Model 1 and Model 5. (a) MLP with Model 1, (b) MLP with Model 5 (c) LSTM with Model 1, (d) LSTM with Model 5, (e) LSTM-MLP with Model 1, and (f) LSTM-MLP with Model 5

The RMSE value as an evaluation of accuracy and error depends on the distribution of input values. As seen in Fig. 6, the value 0 has occurred in some data, giving rise to outlier values. Outlier values can affect the accuracy of the results and increase the RMSE value. Meanwhile, the MAE values based on Table 1 are generally smaller than the RMSE values because the outlier distribution has little effect on the accuracy and error values based on MAE[51].

The wind power prediction with LSTM method shows 1.9% accuracy improvement in average with one additional weather data. MLP method yields 2.2%, and LSTM-MLP yields 2.9% accuracy improvement. In average, one additional weather data could improve wind power prediction at 2.3% more accurate.

From the results of wind power and wind speed estimates for the five combinations, the RMSE value is better than Samadianfard[52], even though the dataset is larger, namely 3,611 meteorological data. But on the other hand, the error value based on RMSE can also be increased by making adjustments to the hyper-parameters so that it can produce better accuracy as done by Nkeng Matip[53], by determining the learning step or learning rate so that the RMSE value is below 0.1.

5. Conclusion

In this study, artificial neural networks (ANNs) specifically Long Short-Term Memory (LSTM) and Multi-Layer Perceptron (MLP) of Deep Learning are used to examine the effects of various meteorological data on wind speed prediction. The combination with most of the weather data considered as inputs yields the lowest RMSE and MAE values, per the results. It is also can be concluded that additional weather data, even though they show almost no correlation to wind power in Baron Techno Park as shown in FIGURE 2, can improve short-term wind power prediction. The wind power prediction using additional weather data is showing 2.3% improvement, with every addition of weather parameter.

Short-term wind prediction is essential for microgrid scheduling and improving decisions in microgrid power control. Future works may include increasing the number of datasets, tuning the hyper-parameter of the Deep Learning architecture, and normalization data. These actions will enhance the accuracy of wind forecasting so it could also be expected to be able to predict weather extremes such as wind storms, which may have caused the wind turbine malfunction in 2019.

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