Short-Term Forecasting Models of Wind-Speed for Airborne Wind Turbines: A Comparative Study

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Abstract*—The technology of airborne wind turbines is rapidly growing, with the purpose of overcoming working limitations of wind turbines at low altitudes. High-altitude wind is strong enough for efficient power generation, but wind conditions vary. Wind-speed forecasting in real time is necessary for power generation or flight stabilization. This study investigates three widely used forecasting models with a single-step and multistep ahead scheme for short-term wind-speed prediction from historical wind measurement data: a persistence model, an autoregressive moving average (ARMA) model, and an artificial neural network (ANN). In the single-step scheme, the accuracy of the persistence model dramatically decreases as the time horizon increases; nevertheless, the persistence model is the simplest algorithm to implement. The ARMA model and the ANN yield a significant accuracy of wind-speed forecasting, compared with the persistence model. The overall mean absolute errors (MAEs) of ARMA and ANN are 19.78% and 22.69% lower than that of the persistence method, respectively. The lowest errors were found in ANNs for most cases of time horizon lengths. Unlike ANNs, the setup of the ARMA model is systematical. A few time horizons can be recommended for short-term wind-speed forecasting for an airborne wind turbine. However, for a long time horizon, the multistep ahead forecasting scheme is recommended since the overall MAEs from the ARMA and ANN are reduced by 4.70% and 11.88%, respectively.

***Index Terms*—Airborne wind turbine, wind forecasting, persistence model, autoregressive moving average model, artificial neural network.**

I. Introduction

In wind energy technology, it is commonly known that wind turbines are used to capture wind energy and convert it into electrical energy via an electrical generator. According to the power law [1], wind at a high elevation is exponentially stronger than that at a low elevation. Therefore, airborne wind turbines can be installed at high altitudes since they have accessibility to high wind energy [2]. Figure 1 illustrates the installation of a Kytoon-type airborne wind turbine. A wind turbine is installed within the shroud of a balloon-like aircraft that drifts in the sky. Wings are designed for automatic airborne control in the direction against the wind.

Since wind at high altitudes is strong but not consistent all the time [3], wind forecasting in real time is necessary for stabilizing airborne wind turbines. In [4], statistical schemes were found to be suitable for short-term forecasting, from thirty minutes to six hours ahead because of the simplicity of implementation. This study investigates three widely used models for the feasibility of short-term wind-speed forecasting: a persistence model, an autoregressive moving average (ARMA) model, and an artificial neural network (ANN). The persistence model is the simplest technique, which is suitable for a short time horizon. In addition, it is regarded as a benchmark to evaluate the performance of other forecasting models [5]. The ARMA model is one of the most widely used time-series models to predict future data [6]. It is a linear mathematical model, which is superior in terms of accuracy of forecasting, with a longer time horizon than the persistence method [7, 8]. Due to its linearity, applications of the ARMA model are efficient for variable data at given operating conditions [9]. ANNs fundamentally predict the behavior of data information based on training data of past records [10]. Unlike the ARMA model, the ANN is considered as a nonlinear mathematical model. Compared to the persistence model and ARMA model, the performance of the ANN in forecasting is enhanced, as many real systems possess nonlinearity and uncertainty [11]. Feed-forward ANNs are one of the most widely used models for forecasting because of their simplicity [12]. Those forecasting models are usually implemented with either single-step or multistep ahead forecasting [13]. The single-step scheme is a conventional approach where historical data is used to estimate future data, but the multistep scheme makes use of forecasted data together with historical data to predict future data.

In this study, wind-speed data is used for a comparative investigation of short-term wind-speed forecasting models for airborne wind turbines. A single-step scheme is applied to investigate the forecasting

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performance of the persistence model, ARMA model, and ANN in an hour to six hours ahead, as a benchmark. A multistep scheme of six-hour-ahead forecasting is used to investigate whether performance can be improved for a long time horizon.

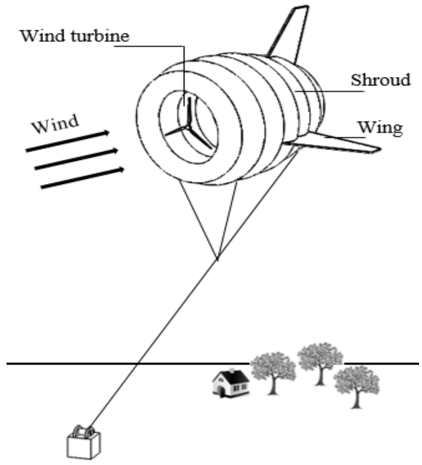

Figure 1. Kytoon-type airborne wind turbine.

II. METHODOLOGY

A. Persistence Model

The persistence model is the simplest forecasting technique. It is assumed that the data at the next time is the same as the data at the present time [14]. The persistence model can be written as

$$v_{t+\Delta t} = v_t \tag{1}$$

where $v_{t+\Delta t}$ is the data at the next time $t+\Delta t$, v_t is the data at the current time t, and Δt is the forecasting horizon.

The forecasting horizon Δt is usually the sampling time of the wind measurement. It can be noticed that the persistence model can work reasonably if the data has a low variance. In addition, by forecasting in a very short time horizon, the persistence model often yields acceptable predictions.

B. ARMA Model

The ARMA model is a time-series model in statistical analysis. The principle of the ARMA model is that data at the next time has a correlation of past data in the time series with two parts: (1) autoregressive part and (2) moving average part [15]. In the autoregressive part, data at the next time can be extrapolated from a linear combination of past data in the time series. The moving average part involves a linear combination of white noise errors. The ARMA model is typically referred to in [16]

$$v_{t+\Delta t} = \mu + e_t + \sum_{i=0}^{p-1} \varphi_i v_{t-i\Delta t} + \sum_{i=0}^{q-1} \phi_i e_{t-i\Delta t} \tag{2}$$

where p is the order of the autoregressive part, q is the order of the moving average part, μ is the parametric constant, φ_i is the parameter of the autoregressive part, ϕ_i is the parameter of the moving average part, and e is the white noise.

It is known that the forecasting performance depends on how the model is fit to the data. Hence, there is a need to select proper orders p and q using the Bayesian Information Criterion (BIC) [17]. The model parameters μ, φ_i, and ϕ_i can be estimated using maximum likelihood estimation [18].

C. ANN

Unlike the ARMA model, the ANN has inherent nonlinear forecasting. It is a mathematical approach for computing information on the basis of a large collection of neurons, which mimic how a human brain performs learning [19]. Knowledge is captured by weights and biases of neurons, which are represented by cycles in Figure 2. In this study, we apply a widely used feed-forward type of ANNs with n present and past input data points. Information of the current and past data forwardly moves from the input layer through the hidden layer to the output layer of data.

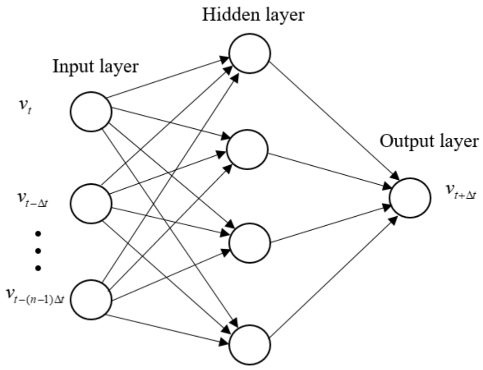

Figure 2. Schematic diagram of a feed-forward ANN.

The next data point can be predicted by the feed-forward ANN function in

$$v_{t+\Delta t} = f\left(v_t, v_{t-\Delta t}, \ldots, v_{t-(n-1)\Delta t}, w, b\right) \tag{3}$$

where w represents the weights of neurons and b represents the biases of neurons.

Let $v_{t-(i-1)\Delta t}$ be x_i of the ANN model in Eq. (4). From the input layer to the hidden layer, the hidden layer value y_j at node j in the hidden layer is computed by

$$y_j = f\left(\sum_{i=1}^{n} x_i w_{ij} + b_j\right) \tag{4}$$

where x_i is the input value at node i in the input layer, w_{ij} is the weight between node i in the input layer and node j in the hidden layer, b_j represents the biases at node j in the hidden layer, and f is the activation function.

From the hidden layer to the output layer, the output value z_k at node k in the output layer is computed by

$$z_k = f\left(\sum_{j=1}^{m} y_j w_{jk} + b_k\right) \tag{5}$$

where w_{jk} is the weight between node j in the hidden layer and node k in the output layer, b_k represents the biases at node k in the output layer, and m is the number of hidden layer units.

Before forecasting, learning is performed with a set of past data [20]. In this work, the weights and biases of the ANN are recursively adjusted by the Levenberg–Marquardt back-propagation algorithm to minimize the error between the predicted data and the actual data [21].

D. Single-Step Ahead Forecasting

In single-step ahead forecasting, the measurement data of wind-speed is directly inputted to the forecasting models so as to predict future data of wind-speed, as written in

$$v_{t+\Delta t} = f\left(v_t, v_{t-\Delta t}, \cdots, v_{t-(n+1)\Delta t}\right) \tag{6}$$

E. Multistep Ahead Forecasting

In multistep ahead forecasting, the predicted values are also used as input data. The value of h-step ahead forecasting $v_{t+h\Delta t}$ can be determined in a time series from the first step to the hth step by

$$v_{t+\Delta t} = f\left(v_t, v_{t-\Delta t}, \cdots, v_{t-(n-1)\Delta t}\right) \tag{7}$$

$$v_{t+2\Delta t} = f\left(v_{t+\Delta t}, v_t, v_{t-\Delta t}, \cdots, v_{t-(n-2)\Delta t}\right) \tag{8}$$

$$v_{t+3\Delta t} = f\begin{pmatrix} v_{t+2\Delta t}, v_{t+\Delta t}, v_t, v_{t-\Delta t}, \cdots, \\ v_{t-(n-3)\Delta t} \end{pmatrix} \tag{9}$$

$$\vdots$$

$$v_{t+h\Delta t} = f\begin{pmatrix} v_{t+(h-1)\Delta t}, v_{t+(h-2)\Delta t}, \cdots, \\ v_{t+\Delta t}, v_t, v_{t-\Delta t}, \cdots, v_{t-(n-h)\Delta t} \end{pmatrix} \tag{10}$$

III. Results and Discussion

A. Data Preparation

In order to investigate the performances of the persistence model, the ARMA model and the ANN are used for short-term wind-speed forecasting at the operating height of airborne wind turbines of around 100 m. Hourly mean wind-speed data is recorded from a 120 m wind mast at Thammasat University as shown in Figure 3. The wind-speed data is separated into two sets. The first four-week data is used to determine the model parameters of the ARMA model and the weights as well as biases of the ANN. The other wind-speed data is used to validate the forecasting performance of each model. Figure 4 shows the probability distribution of wind-speed data with an average speed of 4.56 m/s and standard deviation of 1.71 m/s.

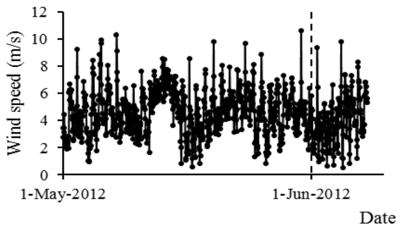

Figure 3. Hourly wind-speed in time-series data.

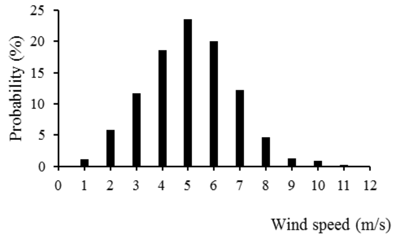

Figure 4. Probability density function of wind-speed data.

B. Forecasting Models with a Single-Step Scheme

The forecasting models are performed an hour ahead and up to six hours ahead to represent short-term wind-speed forecasting. It is remarked that the sampling time is the same as the time horizon. For example, three-hour ahead forecasting requires the sampling time of input data to be three hours. The first four weeks of the wind-speed data are used to determine the model parameters of the ARMA model and the weights and biases of the ANN. By implementing the BIC technique, the best-fit models of ARMA(p,q) are ARMA(1,2), ARMA(2,3), ARMA(1,2), ARMA(5,1), ARMA(4,2), and ARMA (4,3) for one-hour-ahead, two-hour-ahead, three-hour-ahead, four-hour-ahead, five-hour-ahead, and six-hour-ahead forecasting, respectively. The parameters of the ARMA model are summarized in Table I.

TABLE I. Parameters of the ARMA models.

Parameters	Number of hours ahead					
	1	2	3	4	5	6
p	1	2	1	5	4	4
q	2	3	2	1	2	3
μ	0.923	1.445	6.107	0.728	1.039	2.106
φ_1	0.803	1.498	−0.300	0.777	0.876	0.192

φ_2	-	−0.810	-	−0.158	−0.490	−0.308
φ_3	-	-	-	−0.144	0.164	0.300
φ_4	-	-	-	0.095	0.226	0.339
φ_5	-	-	-	0.268	-	-
ϕ_1	0.075	−1.084	0.687	−0.435	−0.548	0.177
ϕ_2	−0.202	0.475	0.366	-	0.114	0.181
ϕ_3	-	0.172	-	-	-	−0.213

In addition, the ANN is trained to determine the number of neurons, weights, and biases for each time horizon. The architecture of the ANN, used for forecasting, is summarized in Table II.

TABLE II. ARCHITECTURE OF THE ANN.

Activation function	Tangent sigmoid
Training algorithm	Levenberg–Marquardt
Performance function	Mean square error
Number of input layer nodes	3
Number of hidden layer nodes	10
Number of output layer nodes	1

For the best practice in simulation, the values of weights and biases are listed in Tables III–VIII.

TABLE III. WEIGHTS AND BIASES OF THE ANN FOR ONE-HOUR-AHEAD FORECASTING.

j	Weights and biases					
	Input to hidden				Hidden to output	
	w_{1j}	w_{2j}	w_{3j}	b_j	w_{j1}	b_k
1	−1.240	−2.993	1.174	2.421	0.450	−1.160
2	−1.708	2.448	−0.074	1.952	0.620	
3	0.234	−0.861	3.347	−2.015	−0.060	
4	2.445	−0.065	0.656	−1.949	0.232	
5	−1.185	1.566	2.905	0.402	−0.150	
6	−2.867	3.188	2.930	−0.056	0.222	
7	1.027	−1.655	1.992	0.284	0.514	
8	1.010	−3.710	1.381	2.099	−0.371	
9	−2.360	−3.307	−1.103	−2.852	0.047	
10	−2.427	−2.583	−0.517	−1.876	−0.081	

TABLE IV. WEIGHTS AND BIASES OF THE ANN FOR TWO-HOUR-AHEAD FORECASTING.

j	Weights and biases					
	Input to hidden				Hidden to output	
	w_{1j}	w_{2j}	w_{3j}	b_j	w_{j1}	b_k
1	−0.984	0.212	−1.995	0.944	−0.429	−3.150
2	9.756	−5.798	−2.070	−1.956	−0.013	
3	−1.393	1.198	1.869	−2.478	−0.156	
4	−0.665	3.993	−0.111	−0.907	0.044	
5	−4.979	1.675	−0.786	−0.602	0.133	
6	−3.489	0.255	4.545	−1.770	0.033	
7	0.749	−1.484	2.239	1.473	0.420	
8	3.546	−4.174	−1.338	2.292	−0.160	
9	−0.017	3.307	4.596	7.590	−1.758	
10	1.842	1.601	0.943	2.196	0.269	

TABLE V. WEIGHTS AND BIASES OF THE ANN FOR THREE-HOUR-AHEAD FORECASTING.

j	Weights and biases					
	Input to hidden				Hidden to output	
	w_{1j}	w_{2j}	w_{3j}	b_j	w_{j1}	b_k
1	−2.199	2.060	−0.532	4.680	−1.064	0.081
2	0.341	−0.748	4.245	−3.899	−0.237	
3	3.713	0.219	7.377	−1.000	−0.027	
4	−0.104	−0.447	1.605	1.290	1.114	
5	0.776	3.266	−1.299	−0.379	0.069	
6	2.610	4.589	1.958	0.457	−0.037	
7	1.897	2.147	1.425	1.977	0.034	
8	−0.141	0.449	−5.359	−2.940	0.425	
9	0.254	−2.269	−1.895	−2.330	−0.287	
10	3.958	−0.784	1.884	5.147	−0.180	

TABLE VI. WEIGHTS AND BIASES OF THE ANN FOR FOUR-HOUR-AHEAD FORECASTING.

j	Weights and biases					
	Input to hidden				Hidden to output	
	w_{1j}	w_{2j}	w_{3j}	b_j	w_{j1}	b_k
1	−1.342	3.966	−4.788	−0.863	0.206	−0.885
2	−0.076	5.232	0.764	2.377	0.002	
3	−0.602	−0.622	−1.597	0.097	−1.208	
4	–	−1.899	0.552	−0.609	0.016	
5	1.186	2.578	1.627	−0.022	−0.650	
6	−0.736	1.529	−0.720	0.432	0.447	
7	−2.476	3.797	−2.072	−0.866	−0.204	
8	−2.011	−3.721	1.791	−2.426	0.458	
9	−0.660	0.252	−2.071	−0.191	−0.107	
10	−2.028	−1.552	2.106	−2.092	−0.379	

TABLE VII. WEIGHTS AND BIASES OF THE ANN FOR FIVE-HOUR-AHEAD FORECASTING.

j	Weights and biases					
	Input to hidden				Hidden to output	
	w_{1j}	w_{2j}	w_{3j}	b_j	w_{j1}	b_k
1	0.324	0.256	−2.953	−2.830	−0.569	
2	0.864	−2.887	1.517	−0.987	0.178	
3	−2.303	1.985	3.332	0.465	−0.094	
4	2.377	−2.942	0.167	−1.174	−0.171	
5	4.885	0.890	−1.184	0.054	0.185	−0.256
6	1.437	2.614	−1.542	−0.554	0.045	
7	0.633	0.851	−4.751	−1.095	−0.076	
8	2.288	2.823	−2.971	−0.634	−0.193	
9	−2.205	−0.185	1.100	−4.216	0.334	
10	2.934	−1.205	0.383	4.273	0.080	

TABLE VIII. WEIGHTS AND BIASES OF THE ANN FOR SIX-HOUR-AHEAD FORECASTING.

j	Weights and biases					
	Input to hidden				Hidden to output	
	w_{1j}	w_{2j}	w_{3j}	b_j	w_{j1}	b_k
1	2.330	2.051	0.384	−2.736	−0.752	
2	−2.120	2.537	1.732	2.918	0.036	
3	−0.362	2.548	0.651	−2.108	0.520	
4	−0.356	−0.912	2.882	1.315	0.299	
5	−2.235	−2.874	−2.915	0.996	−0.190	−0.072
6	1.265	−1.626	−1.934	0.443	0.367	
7	−1.950	−1.517	2.115	−1.347	0.197	
8	−0.526	3.705	−1.669	2.740	0.612	
9	1.791	2.411	0.530	3.478	−0.704	
10	0.552	1.121	1.556	3.598	0.013	

From Figure 5–10, plots of the one-hour-ahead up to six-hour-ahead forecasting are presented, compared to the actual wind-speed data during a week. It is obvious that the predicted wind-speed data from the persistence method, the ARMA model, and the ANN at a short time horizon, such as one-hour-ahead and two hours ahead, provide better fits to the actual wind-speed data than at a long time horizon. It is difficult for forecasting models to mimic the dynamic behaviors of wind-speed data as the time horizon increases.

In order to determine the forecasting accuracy, criteria of mean absolute error (MAE) and root mean square error (RMSE) are applied in this study. The MAE is defined as the average of the absolute error between the predicted data and the actual data. The RMSE is defined as the standard deviation of the error between the predicted data and the actual data. The lower the values of the MAE and RMSE, the higher the forecasting accuracy.

Figure 11 and 12 show the MAE and RMSE values of the three forecasting models with respect to the different time horizon from one to six hours ahead. It is shown that the persistence model predicts the wind-speed reasonably at one-hour-ahead forecasting as the values of MAE and RMSE are not significantly higher than those of the ARMA model and the ANN. However, the values of MAE and RMSE of the persistence model rapidly increase at a higher time horizon. Both the ARMA model and the ANN provide acceptable accuracies from two hours ahead compared to the persistence model. Furthermore, in most cases, the ANN yields a higher accuracy than the ARMA model. This can be interpreted as that the characteristics of the wind-speed data are nonlinear, where the ANN is more − than the ARMA model. The overall MAEs of the ARMA and ANN are 19.78% and 22.69% lower than that of the persistence method, respectively. The overall RMSEs of the ARMA and ANN are 20.39% and 25.30% lower than that of the persistence method, respectively.

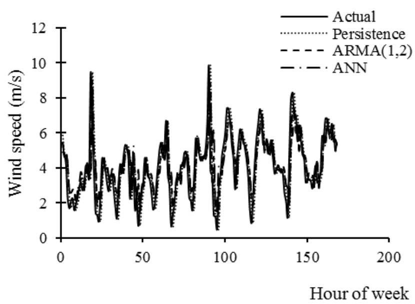

Figure 5. Plots of one-hour-ahead predicted data with actual data.

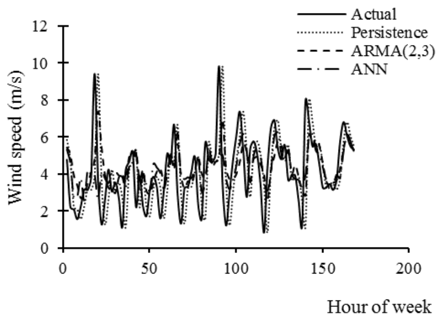

Figure 6. Plots of two-hour-ahead predicted data with actual data.

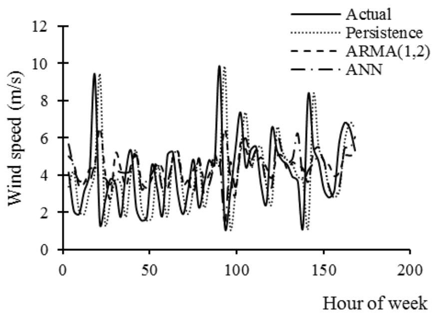

Figure 7. Plots of three-hour-ahead predicted data with actual data.

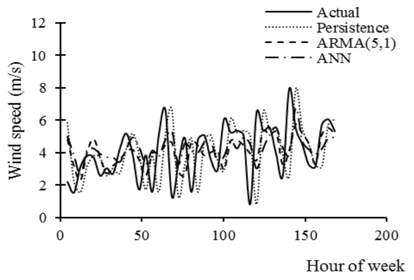

Figure 8. Plots of four-hour-ahead predicted data with actual data.

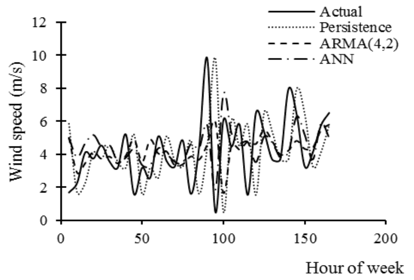

Figure 9. Plots of five-hour-ahead predicted data with actual data.

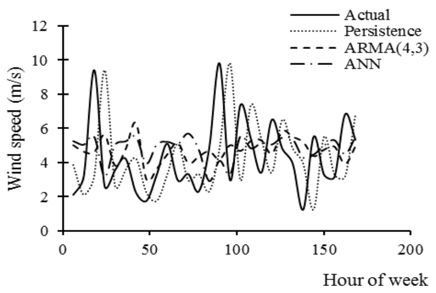

Figure 10. Plots of six-hour-ahead predicted data with actual data.

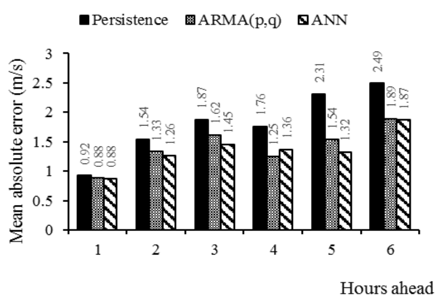

Figure 11. Comparison of MAEs of different forecasting models at different time horizons.

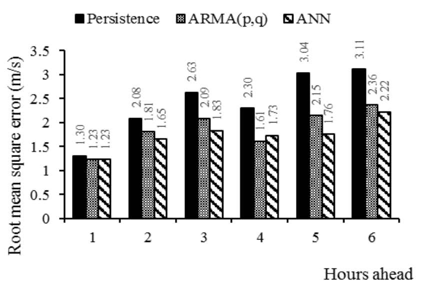

Figure 12. Comparison of RMSEs of different forecasting models at different time horizons.

C. Forecasting Models with a Multistep Scheme

From Figure 11 and 12, it can be noticed that the accuracy of the predictions decreases as the time horizon increases. An alternative way to improve accuracy is to perform multistep ahead forecasting for a long time horizon. The forecasting models of ARMA and ANN with a multistep scheme are implemented to predict the wind-speed for six hours ahead using Eqs. (7)–(10). It should be remarked that the persistence model yields results similar to those of the single-step scheme.

In Figure 13 and 14, plots of the six-hour-ahead forecasting of the ARMA and ANN are presented, respectively, compared with measurement data. It can be seen that the predicted wind-speed data from the ARMA model and the ANN are better fitted to actual wind-speed data than the single-step scheme. At a long time horizon, the multistep scheme uses the predicted data of wind-speed to forecast future dynamics of wind-speed.

Figure 15 and 16 show the values of MAE and RMSE from the ARMA models and the ANN at different steps. The multistep scheme is capable of improving the prediction accuracy, compared with the single-step scheme. Satisfactory results of the ARMA model and the ANN are shown at six-step and three-step forecasting, respectively. The ARMA model improves the forecasting accuracy with an MAE of 4.70% and an RMSE of 5.15%, and the ANN increases the forecasting accuracy with an MAE of 11.88% and an RMSE of 8.65%.

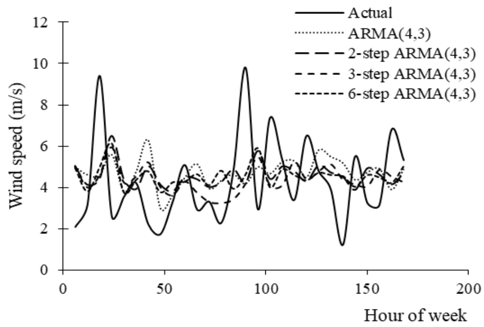

Figure 13. Plots of six-hour-ahead predicted data by the ARMA model with actual data.

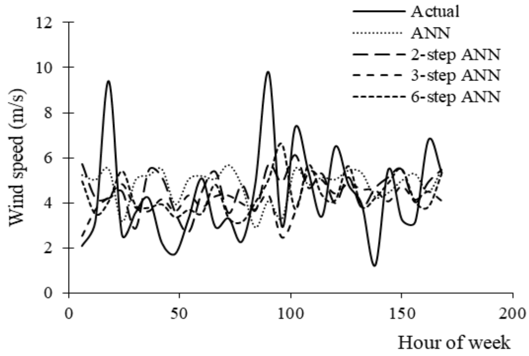

Figure 14. Plots of six-hour-ahead predicted data by the ANN model with actual data.

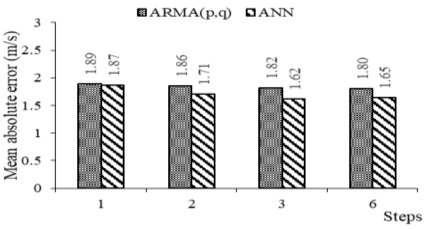

Figure 15. Comparison of MAEs of different forecasting models with multistep schemes.

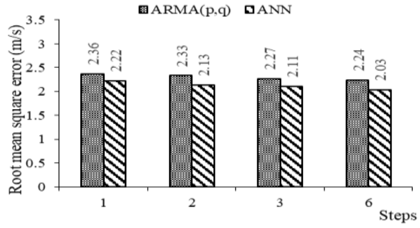

Figure 16. Comparison of RMSEs of different forecasting models with multistep schemes.

IV. Conclusion

When dealing with unknown wind conditions, forecasting models show differences in the forecasting accuracy and are hence difficult to implement. From comparative investigations, the persistence model was found to be the simplest algorithm to implement reasonable forecasting in a short time horizon. However, it yields a lower accuracy when the time horizon increases. Although the ANN yields the best results in most predictions, it is hard to set up structural parameters such as the number of neurons, weights, and biases, compared with other models. On the other hand, the ARMA model provides a trade-off between accuracy and difficulty of implementation. In addition, the ARMA model and ANN can be applied with a multistep scheme, which is capable of improving the forecasting accuracy, compared to the single-step scheme. Reliable short-term wind-speed forecasting with different time horizons has benefits to airborne wind turbines, for flight stabilization and power generation at high altitudes.

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