Multi-Time Series and -Time Scale Modeling for Wind Speed and Wind Power Forecasting

Part I: Statistical Methods, Very Short-Term and Short-Term Applications

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***Abstract*—This study concentrates on multi-time series and -time scale modeling in wind speed and wind power forecasting. Different statistical models along with different time horizons are analyzed and evaluated broadly and comprehensively. For this reason, the entire study is divided into two main scientific parts. In case of making a general overview of the entire study, moving average (MA), weighted moving average (WMA), autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) methods are employed for multi-time series modeling. Very short-term, short-term, medium-term and long-term scales are utilized for multi-time scale modeling. Specifically, in this part of the entire study, the mentioned statistical models are presented in detail and 10-min and 1-h time series forecasting models are created for the purpose of achieving 10-min and 2-h ahead forecasting, respectively. Many useful outcomes are accomplished for very short-term and short-term wind speed and wind power forecasting.**

Keywords-Statistical methods; forecasting; very short-term; short-term; wind speed; wind power

I. INTRODUCTION

As a green energy source, there has been a growing interest in generating electricity from wind energy in the last two decades. In 2014, more than 51 GW of wind power capacity was added around the world and the total installed wind power capacity reached above 369 GW in the world [1, 2]. This means that the cumulative market growth was more than 16% at the end of the 2014. However, the greatest problem of wind power integration to the existing power system is intermittent and variable nature of wind power due to the high correlation with stochastic nonstationary of wind speed [3]. For this reason, a reliable and decisive wind speed and wind power forecasting approach is a fundamental necessity for mitigating the undesirable results in wind energy conversion systems.

Various methods have been proposed for dealing with wind speed and wind power forecasting. Three mainstream approaches in this field are physical modeling, statistical modeling and soft computing models. Physical methods utilize the detailed physical description for modeling the on-site conditions at the location of the wind farm [4]. Some of them are Hirlam [5], Previento [6], LocalPred [7], etc. Statistical methods also make forecasts analyzing historical data and achieve good results when the data show linearity and stationarity [8]. The widely used of them are ARMA, ARIMA, Kalman filters, grey predictors, etc. [9]. Soft computing methods are based on collecting input/output data pairs and learning the proposed network from these data [10]. Fuzzy logic, artificial neural networks, adaptive neuro-fuzzy inference systems and metaheuristic intelligence are among the soft computing methods [11]. On the other hand, four mainstream horizons are typically used in wind speed and wind power forecasting. These are categorized as very short-term (few seconds to 30 min), short-term (30 min to 6 h), medium-term (6 h to 1 day) and long-term (1 day to 1 week) scales [9, 12]. Each horizon has its own intended purpose. Very short-term and short-term horizons are used for turbine control, load tracking and pre-load sharing while medium-term and long-term horizons are utilized for power system management, energy trading, maintenance and repair of wind turbines [12, 13]. Several applications related to the different forecast horizons are available in the literature [14-16].

In spite of growing awareness in wind speed and wind power forecasting in terms of methods and horizons employed, there are limited studies in the literature that particularly focusing on the forecasting performance of statistical models on the basis of different time scales. The main contribution of the entire study (that means two parts of the study) is to investigate the forecasting accuracy of MA, WMA, ARMA and ARIMA models for very-short term, short-term, medium term and long-term scales in a detail manner. In addition, the wind speed and wind power dataset used in the entire study was obtained from the Database on Wind Characteristics [17]. The related wind turbine is placed in Tjæreborg, Denmark and it has a rated power of 2 MW.

II. TIME SERIES FORECASTING MODELS

A time series is a collection of data recorded over a period of time such as every second, minute, hour, etc. So, time series forecasting concentrates on identifying future events based on known events, usually recorded at uniform time intervals [18].

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In this paper, moving average, weighted moving average, autoregressive moving average and autoregressive integrated moving average models are used for multi-time series modeling. In here, mean absolute percentage error (MAPE) is employed for measuring the forecast performance of time series forecasting models [19]. Moreover, the time series forecasting models employed are checked against the persistence model in terms of the improvement percentage of forecasting accuracy. It is based on setting the predicted value at the current value within the prediction horizon [20].

A moving average model captures serial autocorrelation in a time series y_t by denoting the conditional mean of y_t as a function of past innovations, $\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-q}$. The form of the $MA(q)$ is expressed as below, where ε_t is an uncorrelated innovation process with mean zero and c is the unconditional mean of y_t [21]. A simple moving average of span N assigns weights $1/N$ to the most recent N observations. However, the weighted moving average model selects a different weight for each data and then computes a weighted average of the most recent N observations [22].

$$y_t=c+\varepsilon_t+\theta_1\varepsilon_{t-1}+\ldots+\theta_q\varepsilon_{t-q} \quad (1)$$

In MA and WMA models, the importance of the predictors (present and past values) is ranked in the order of time sequence [23]. In case of considering a large number of predictors, the importance index decreases and the poor forecast performance occurs due to the course of dimensionality [24]. For this reason, the last 10 observations in the total dataset were used heuristically as the most important predictors in MA and WMA models. In addition, the weights used for the last 10 observations in WMA model are summarized in Table I. It should be noted that the total weight equals to 1 for all predictors. *x(t), x(t-k), …, x(t-9k)* represent the current and past observed parameters in this table.

TABLE I. THE WEIGHTS USED FOR PREDICTORS

Predictor	Weight	Predictor	Weight	Predictor	Weight
x(t)	0.182	x(t-4k)	0.109	x(t-8k)	0.036
x(t-k)	0.164	x(t-5k)	0.091	x(t-9k)	0.018
x(t-2k)	0.145	x(t-6k)	0.073	-	-
x(t-3k)	0.127	x(t-7k)	0.055	-	-

An autoregressive moving average process states the conditional mean of y_t as a function of past observations, $y_{t-1}, y_{t-2}, \ldots, y_{t-p}$, and past innovations, $\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-q}$. The number of past observations and innovations, p and q, represent the autoregressive and moving average degrees, respectively. In general, the $ARMA(p,q)$ process is expressed as below, where ε_t is an uncorrelated innovation process with mean zero [25]:

$$y_t=c+\phi_1 y_{t-1}+\ldots+\phi_p y_{t-p}+\varepsilon_t+\theta_1\varepsilon_{t-1}+\ldots+\theta_q\varepsilon_{t-q} \quad (2)$$

An autoregressive integrated moving average process generates nonstationary series integrated of order d. This nonstationary process is made stationary by taking d differences. A series modeled as a stationary $ARMA(p,q)$

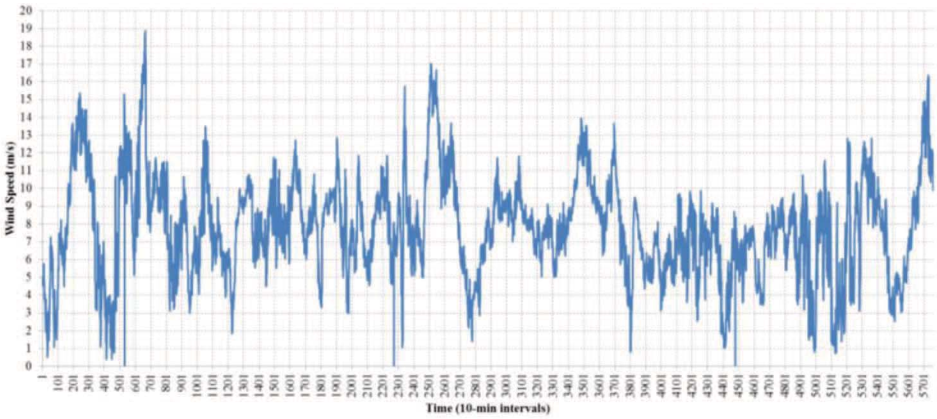

Fig. 1. Wind speed time series at 10-min intervals

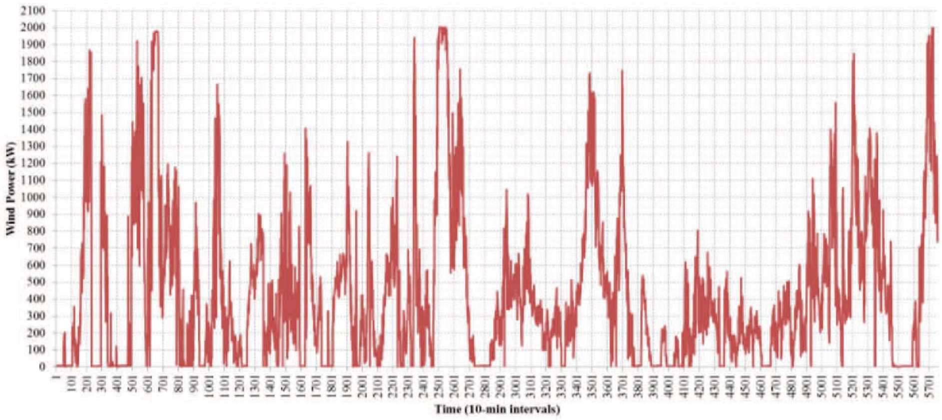

Fig. 2. Wind power time series at 10-min intervals

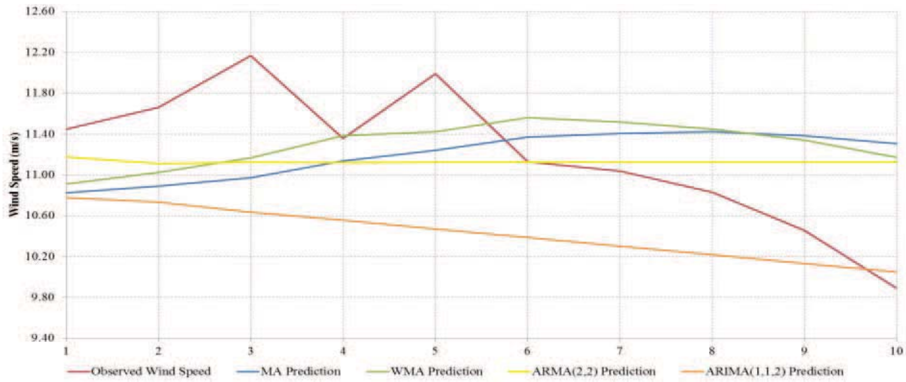

Fig. 3. 10-min ahead forecasting results for wind speed parameter

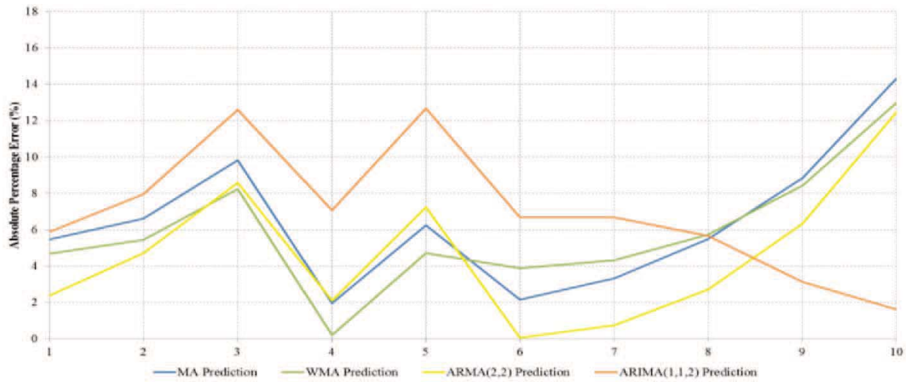

Fig. 4. 10-min ahead forecasting errors for wind speed parameter

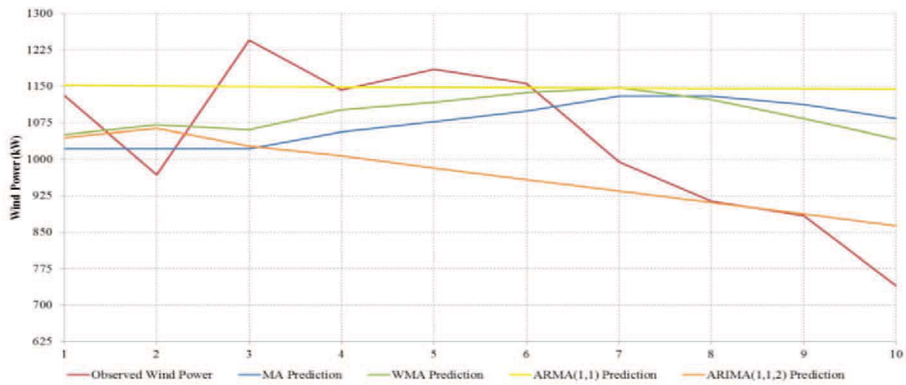

Fig. 5. 10-min ahead forecasting results for wind power parameter

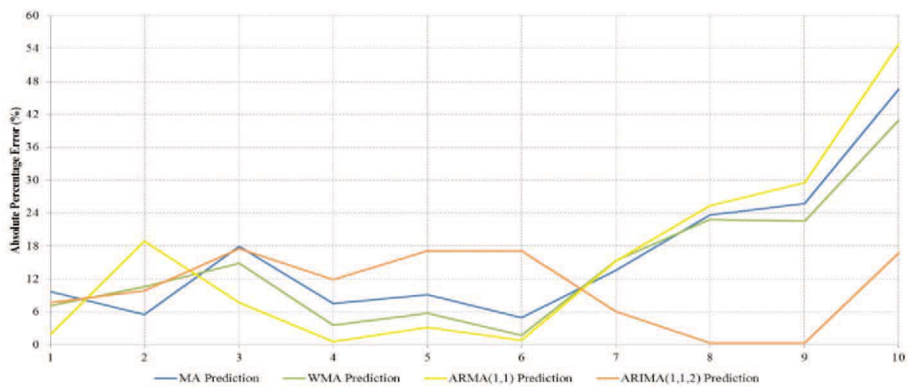

Fig. 6. 10-min ahead forecasting errors for wind power parameter

process after being differenced d times is denoted by *ARIMA(p,d,q)*. It is expressed as below, where ε_t is an uncorrelated innovation process with mean zero and $\Delta^d y_t$ is a dth differenced time series [26]:

$$\Delta^d y_t = c + \phi_1 \Delta^d y_{t-1} + \ldots + \phi_p \Delta^d y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} \quad (3)$$

ARMA(1,1), ARMA(1,2), ARMA(2,1) and ARMA(2,2) models in ARMA analyses and ARIMA(1,1,1), ARIMA(1,1, 2), ARIMA(1,2,1), ARIMA(2,1,1), ARIMA(1,2,2), ARIMA(2, 1,2), ARIMA(2,2,1) and ARIMA(2,2,2) models in ARIMA analyses are employed in this research. Other ARMA and ARIMA models are not employed due to their high error rates. In the next section, the ARMA and ARIMA models that have the lowest mean absolute percentage errors are considered in each forecasting approach.

III. Very Short-Term Forecasting Results

The total dataset used for very short-term forecasting has 5760 data points for each parameter. The wind speed and wind power values recorded at 10-min intervals are illustrated in Figures 1 and 2, respectively. In these figures, the maximum values are measured as 18.88 m/s for wind speed and 2004.31 kW for wind power.

10-min ahead forecasting results and errors for wind speed parameter are given in Figures 3 and 4, respectively. ARMA(2,2) model outperforms MA, WMA and ARIMA(1,1,2) models in terms of the forecasting accuracy. The error rates are achieved as 4.73%, 6.42%, 5.86% and 6.99%, respectively. ARIMA(1,1,2) model provides the worst forecasting accuracy. In addition, 10-min ahead forecasting results and errors for wind power parameter are presented in Figures 5 and 6, respectively. Differently, ARIMA(1,1,2) model surpasses MA, WMA and ARMA(1,1) models in terms of the forecasting performance. The error values are obtained as 10.45%, 16.42%, 14.50% and 15.77%, respectively. MA model produces the largest prediction errors. However, in case of comparing the best models in 10-min ahead forecasting with the persistence model, the improvement percentages of ARMA(2,2) and ARIMA(1,1,2) models are computed as -11.96% and 4.78%, respectively. As a result, it is obvious that the persistence model comes into prominence in 10-min ahead wind speed forecasting while it is the ARIMA(1,1,2) model in 10-min ahead wind power forecasting.

IV. Short-Term Forecasting Results

Every six consecutive data points in the 10-min time series dataset are aggregated into a mean hourly value and so, the final dataset used for short-term forecasting is resulted in 960 data points for each parameter. The wind speed and wind power values averaged at 1-h intervals are depicted in Figures 7 and 8, respectively. In these figures, the highest values are observed as 17.82 m/s for wind speed and 2001.47 kW for wind power.

2-h ahead forecasting results and errors for wind speed parameter are visualized in Figures 9 and 10, respectively. ARMA(2,2) model predominates MA, WMA and

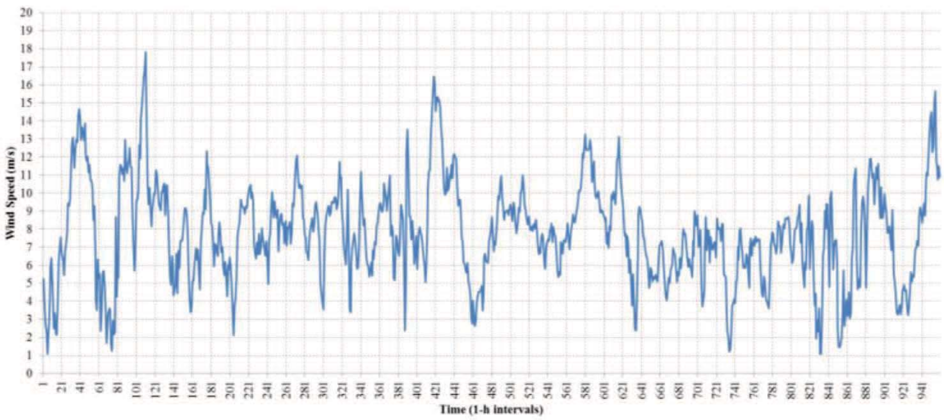

Fig. 7. Wind speed time series at 1-h intervals

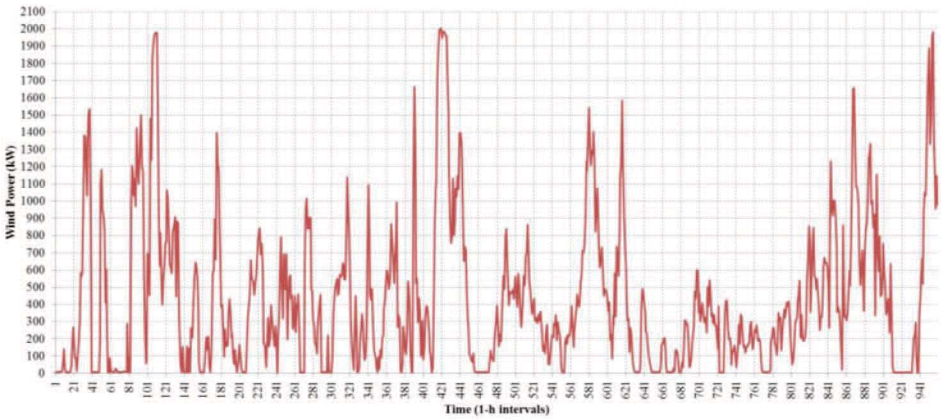

Fig. 8. Wind power time series at 1-h intervals

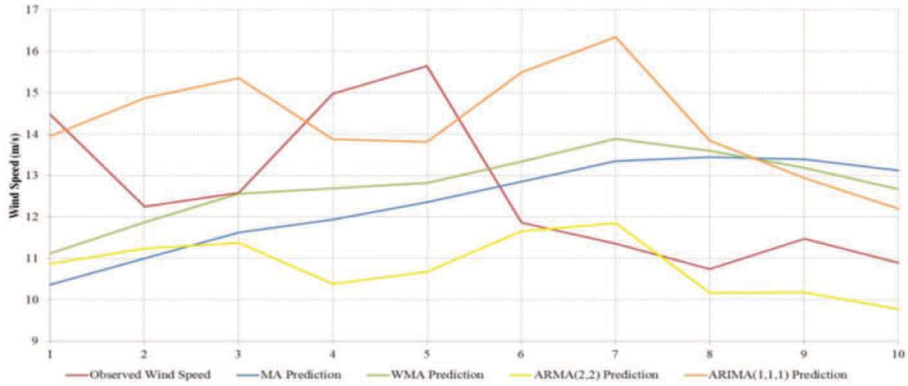

Fig. 9. 2-h ahead forecasting results for wind speed parameter

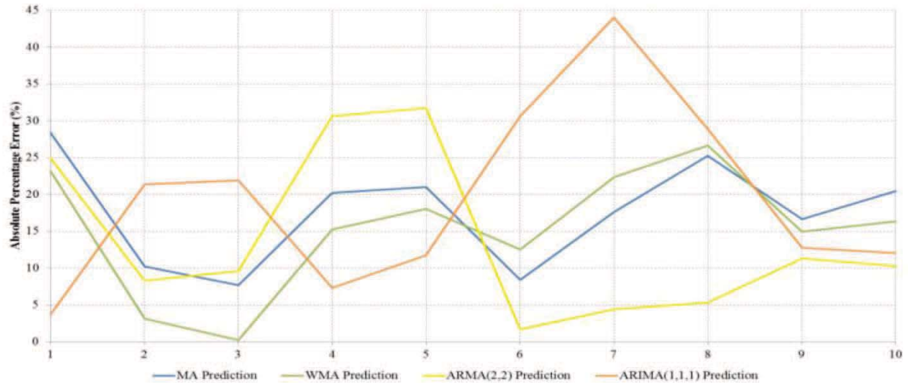

Fig. 10. 2-h ahead forecasting errors for wind speed parameter

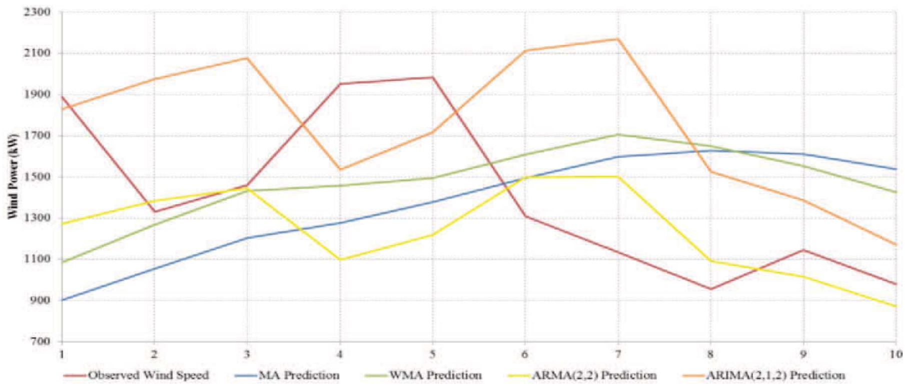

Fig. 11. 2-h ahead forecasting results for wind power parameter

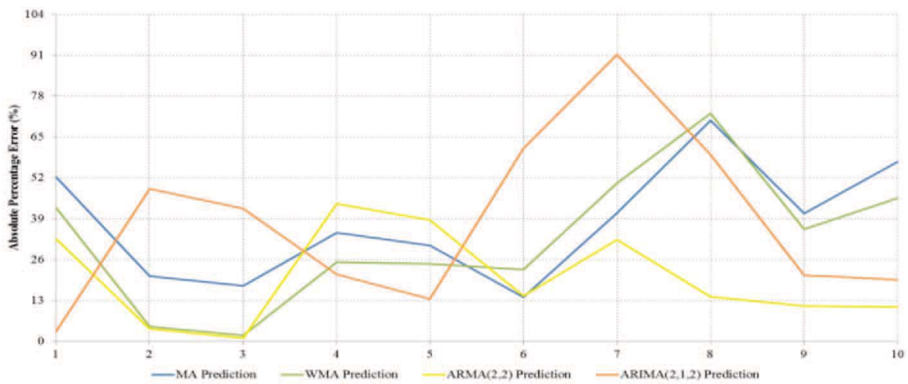

Fig. 12. 2-h ahead forecasting errors for wind power parameter

ARIMA(1,1,1) models on the basis of forecasting accuracy. The error rates are found as 13.81%, 17.60%, 15.27% and 19.43%, respectively. ARIMA(1,1,1) model brings out the most erroneous forecasting accuracy. As well, 2-h ahead forecasting results and errors for wind power parameter are plotted in Figures 11 and 12, respectively. Similarly, ARMA(2,2) model transcends MA, WMA and ARIMA(2,1,2) models on the basis of forecasting performance. The error values are determined as 20.33%, 37.88%, 32.60% and 38.10%, respectively. ARIMA(2,1,2) model creates the most incorrect prediction errors. In case of comparing the best models in 2-h ahead forecasting with the persistence model, the improvement percentages of ARMA(2,2) models are computed as 10.04% and 32.36%, respectively. Last of all, it is plain that ARMA(2,2) model takes attention in 2-h ahead wind speed and wind power forecasting.

V. CONCLUSION

As a first part of the entire study, initially, MA, WMA, ARMA and ARIMA models employed in the paper are described in an explanatory way. In the specific analysis, ARMA(2,2) model is observed as a successful approach by means of producing the lowest MAPEs in 10-min ahead wind speed forecasting and 2-h ahead wind speed and wind power forecasting. Differently, it is the ARIMA(1,1,2) model in 10-min ahead wind power forecasting. However, it should be noticed for the benchmark test that the persistence model ensures better improvement percentage than ARMA(2,2) model in 10-min ahead wind speed forecasting. In addition to these outcomes, ARIMA models demonstrate poor prediction accuracies in 10-min ahead wind speed forecasting and 2-h ahead wind speed and wind power forecasting. It is the MA model in 10-min ahead wind power forecasting.

In the second part [27] of the entire study, the proposed statistical models are analyzed along with medium term and long-term scales for wind speed and wind power forecasting.

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