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Short-term wind speed forecasting using ARIMA model

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The massive integration of wind power into the power system increasingly calls for better short-term wind speed forecasting which helps transmission system operators to balance the power systems with less reserve capacities. The time series analysis methods are often used to analyze the wind speed variability. The time series are defined as a sequence of observations ordered in time. Statistical methods described in this paper are based on the prediction of future wind speed data depending on the historical observations. This allows us to find a sufficiently good model for the wind speed prediction. The paper addresses a short-term wind speed forecasting ARIMA (Autoregressive Integrated Moving Average) model. This method was applied for a number of different prediction problems, including the short term wind speed forecasts. It is seen as an early time series methodology with well-known limitations in wind speed forecasting, mainly because of insufficient accuracies of the hourly forecasts for the second half of the day-ahead forecasting period. The authors attempt to find the maximum effectiveness of the model aiming to find: (1) how the identification of the optimal model structure improves the forecasting results and (2) what accuracy increase can be gained by reidentification of the structure for a new wind weather season. Both historical and synthetic wind speed data representing the sample locality in the Baltic region were used to run the model. The model structure is defined by rows *p*, *d*, *q* and length of retrospective data period. The structure parameters *p* (Autoregressive component, AR) and *q* (Moving Average component, MA) were determined by the Partial Auto-Correlation Function (PACF) and Auto-Correlation Function (ACF), respectively. The model's forecasting accuracy is based on the root mean square error (RMSE), mean absolute percentage error (MAPE) and mean absolute error (MAE). The results allowed to establish the optimal model structure and the length of the input/retrospective period. The quantitative study revealed that identification of the optimal model structure gives significant accuracy improvement against casual structures for 6–8 h forecast lead time, but a season-specific structure is not appropriate for the entire year period. Based on the conducted calculations, we propose to couple the ARIMA model with any more effective method into a hybrid model.

Key words: ARIMA, power system, wind speed, short-term forecasting

INTRODUCTION

Recently, wind power has been growing at an unprecedented rate globally. The increasing importance of wind power integration into the power system encourages researchers to develop more reliable techniques to forecast wind power. To continue the growth in the following decade [1], short-term prediction of wind speed and power generation is becoming increasingly important. However, the reason why generation of wind power is extremely intermittent is that weather conditions and wind speed are highly volatile and affected by a number of factors. As wind energy makes a significant penetration into the electricity grid, the need for accurate predictions of wind power generation becomes critical [2, 3].

Currently, many different methods are used to forecast the wind speed: Autoregressive Moving Average (ARMA), Artificial Neural Networks (ANN), Genetic Algorithm (GA), Wavelet Decomposition (WD), Empirical Mode Decomposition (EMD), Multi-Layer Perceptron (MLP), Extreme Learning Machines (ELM), FUZZY, etc. Studies have shown that hybrid models consisting of a few different methods reach better results than any single model. In recent research, model comparison through the mean absolute percentage error (MAPE) is used for measurement purposes. For example, with a hybrid EMD–ELM model the wind speed forecast average MAPE error is 2.21%, while with a single ELM model it is 8.6% [4–6].

To look for adaptability of an ARIMA model, we need to check if stationary and invertibility conditions are complied with. All ARIMA (0, d, q) models are stationary, but in order to recognize if the model is chosen correctly, we must look if the time series satisfy the other condition – invertibility. Because ARIMA (p, d, 0) models are invertible and based on the values of the parameters, they may not be stationary. As a result, the model has various representations. That is why it is advisable to look for the simplest representations to estimate wind speed.

In 1978, Granger and Andersen proposed a generalized definition of inversion and applied it to linear, non-linear, and bilinear models [7]. It can be seen that some non-linear models are not invertible, but this condition can be achieved with another model's help by combining them together. To define conditions for the general Moving Average (MA) process, of order q, input data should be invertible (accordingly, process borderline should be non-invertible). The conditions have to be termed as acceptability conditions. The dependency can be found on the magnitude of the final moving average parameter, θ_q. If $|\theta_q| < 1$, the process is not acceptable. The process should reach the conditions $|\theta_q| = 1$ for any particular q meaning and is expected to run smoothly. If $|\theta_q| < 1$, the conditions need to be established. Simultaneously, the stationarity of autoregressive processes is examined. In 2008, Ojo compared subset autoregressive integrated moving average models with full autoregressive integrated moving average models [8]. The author estimated and investigated the parameters of these models, and the statistical properties of the derived estimates were set out. He proposed an effective algorithm that can eliminate redundant parameters from the full order ARIMA models.

In this paper, a trial is undertaken to find an appropriate autoregressive integrated moving average (ARIMA) model structure that would be the most efficient and, by comparing forecast and real time series cases, gaining the lowest errors. Research was made to forecast daily wind speed for the first seven days of February 2012 in Latvia by using this model. It is selected to check the model's forecasting performance based on MAPE, RMSE (root mean square error), and MAE (mean absolute error).

To verify if gained results are correct to use, we compared the results of the forecast wind speed for different yearly seasons: winter, spring, summer and autumn. Checking was made by using the gained ARIMA structure (p, d, q) and the same training period for all seasons. Our aim is to research if forecast values combined with real values make sufficiently precise meanings.

METHODOLOGY AND DATA SOURCE

Time series analysis with ARIMA models

Most of the modelling methods, including Box-Jenkins approach [9], are applicable on stationary time series. ARIMA models are a type of time series based on statistical models that are widely used in short-term predictions. A typical

ARIMA model, denoted as ARIMA (p, d, q), can be expressed in the following form:

$$y_t = \text{á} + \sum_{i=1}^{p} \text{ö}_i + \sum_{j=1}^{q} \text{è}_j e_{t-j} + \text{å}_t \qquad (1)$$

This equation can be written as:

$$y_t = \alpha + \phi_i Y_{t-1} + \ldots + \phi_p Y_{t-p} + \\ + \theta_i \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t, \qquad (2)$$

where α is the constant term (i. e. the mean of the underlying stochastic process), ϕ_i is the i-th autoregressive parameter, ϕ_j is the j-th moving average parameter, ε_t is the error term at time t, and y_t is the value of the wind speed observed at the time t [10]. The autoregressive parameters represent the lags of differenced series, and the moving average terms show the lags of the prediction errors. It is possible that the time series data is non-stationary (or seasonal), and in this case it needs to be differenced to become stationary. The result is an "integrated" version of a stationary series, and the model becomes an ARIMA model, denoted by ARIMA (p, d, q), where p, d, and q are the numbers of autoregressive terms, non-seasonal differences, and lagged prediction errors, respectively. Clearly, if d is zero, the ARIMA model becomes an ARMA (p, q) model. If both d and q are zero, then the ARIMA model becomes an AR (p) model. If both d and p are zero, then the ARIMA model becomes a MA (q) model.

In this study, we employ the general procedure of ARIMA modelling for the prediction of wind speed. Based on the data obtained, a suitable model structure and model parameters will be obtained. The procedure is described as follows. Firstly, the stationarity of the time series data is tested by checking the run order plot and Auto-Correlation Function (ACF) plots of the data points. The trends in the time series data and constant variance assumption can be analysed using Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF) plots [11, 12]. Based on certain characteristics of the run order and ACF graphs, successive differencing of the data series might be used until the data is concluded to be stationary. Secondly, the autoregressive and moving average terms can also be determined using the ACF and PACF plots [10, 13]. These graphs are used to make decisions on the autoregressive and moving average terms in the model. Thirdly, based on the identified model structure (p, d, q), the identifying model parameters need to be obtained.

Model precision analysis

The root mean square error (RMSE), mean absolute percentage error (MAPE) and mean absolute error (MAE) are adopted to evaluate the prediction accuracy of the approaches [8]. MAE is a common measure of the forecast error in time series analysis, which measures the average magnitude of the errors in a set of forecasts:

$$\text{MAE} = \frac{1}{n} \sum_{t=1}^{n} |y_t - f_t| \qquad (3)$$

where n is the number of observations in the total evaluation period, y_t is the value of observation at time t, and f_t is the forecast value.

Equation (3) shows that MAE is the average over the absolute values of deviations between the forecast and the corresponding observation [8]. MAPE is calculated as the average absolute percentage error:

$$\text{MAPE} = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{y_t - f_t}{y_t} \right| \qquad (4)$$

As seen in equation (4), the main purpose of MAPE is to show if the data is stable (variation is small). That is why MAPE is important in wind power prediction.

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (y_t - f_t)^2} \qquad (5)$$

Equation (5) indicates that RMSE is a quadratic scoring rule, which measures the average magnitude of the error [8]. The difference between forecasts and corresponding observed values are squared, summed, and then averaged over the sample number. Finally, the square root of the average is taken. Since the errors are squared before they are averaged, RMSE gives relatively high weights to large errors. This means RMSE is most useful when large errors are undesirable.

Wind data

Meteorological data was received from Riga site (central Latvia) [14]. They can be denominated as all-Latvian averages. All variables are presented as hourly data. The investigation period covers the period of 2012.

The research consists of two parts: in the first one we need to reveal the structure of the ARIMA model and in the second to investigate the use of the possibilities. That is why the data that was used in this work can be distributed as values required for structure selection and values for model verification.

For ARIMA model structure selection, the investigation period covers a period of 2 months, from 1 January to 7 February 2012. From 1440 continuous hourly time series data points of wind speed, we used the first 744 to build the prediction models. The remaining 696 data points were used for prediction and performance evaluation.

To build the best model parameters for wind speed forecast, three sets of data were analysed:

- the first (I) period duration is one month (1–31 January 2012),
- the second (II) period duration is 2 weeks (18–31 January 2012), and
- the last (III) period duration is 3 days (29–31 January 2012).

To verify model accuracy in the yearly wind speed forecasting, three more periods were taken to examine the model. These periods include spring, summer and autumn. The wind speed data is taken from the year of 2012. The winter period remains unchanged and is used the same as it is in the selection of the model structure.

RESULTS AND DISCUSSION

Model parameters

To determine the orders, *p* and *q*, the ACF and PACF plots were examined. Figures 1 and 2, respectively, shows the ACF and PACF graphs for the wind speed data.

In Fig. 1 it can be indicated from the PACF plot that the AR (3) model is suitable for the observed data, because of the cut-off at lag 3. ACF

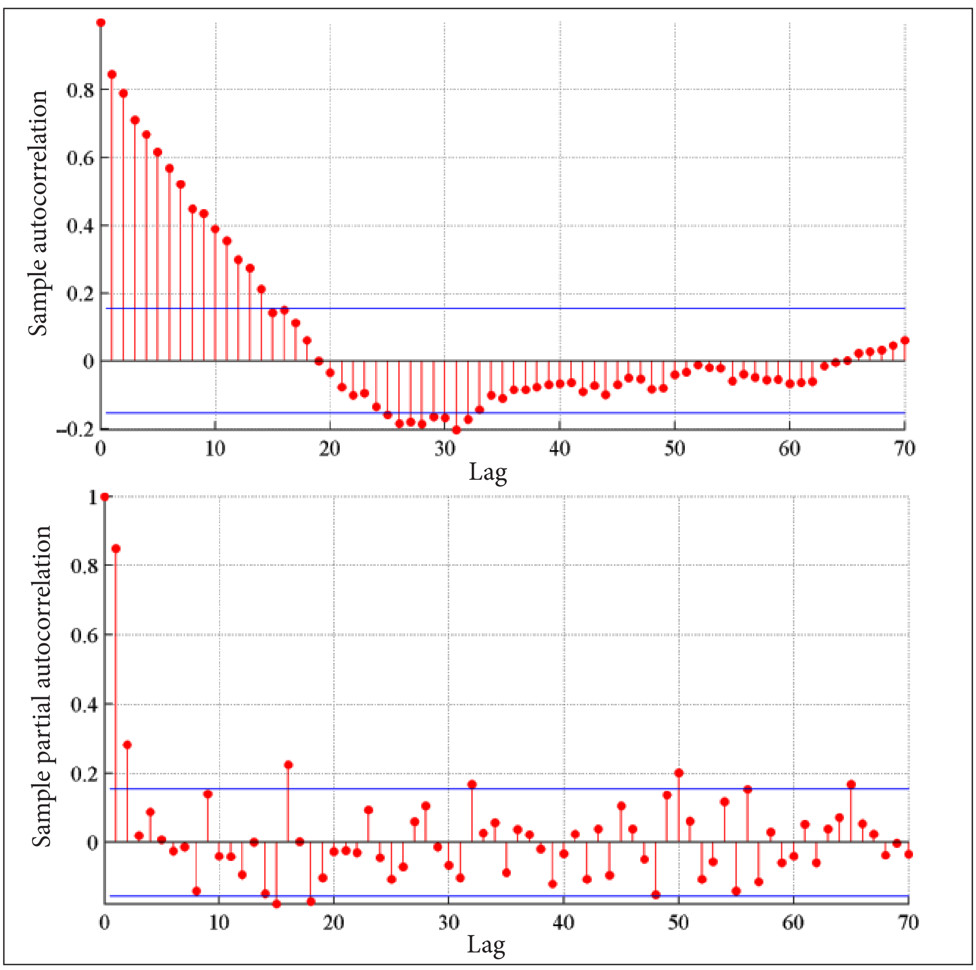

Fig. 1. Autocorrelation and partial autocorrelation functions for observed wind speed data

shows the cut-off at lag 15. That means time series data is non-stationary and needs to be integrated. Figure 2 shows ACF and PACF for integrated wind speed data. It is obvious that integration was needed to make functions stationary.

The analysed partial autocorrelation and autocorrelation functions have not shown the accurate values of *p* and *q* parameters. But as research showed, parameter *d* is needed to be used as 1, because for our time series values stationarity was needed. To find the best model, the parameters *p* and *q* had different values assigned. For each pair of parameters, a new model was constructed. The RMSE has been chosen to compare models with each other. The results are shown in Table 1.

As it is shown in Table 1, the highest value of parameters *p* and *q* is 10 because the model should predict with the lowest error values and should be the simplest one. The higher values of *p* and *q* are inefficient, and the model becomes too complex to calculate and analyse. As it is shown in Table 1, the best model is ARIMA (3, 1, 1). In addition, the model ARIMA (6, 1, 1) predicts wind speed with lower errors. However, the model ARIMA (3, 1, 1) has a simpler construction and the difference of RMSE is not big enough (difference between values is 0.0367) to choose a more complex model.

Our previous investigation of ACF and PACF and RMSE analysis has shown similar results, i. e. ARIMA (3, 1, 1) is one of the best models to describe wind speed data. The higher values of parameters *p* and *q* would lead to a more difficult model. Because of these reasons, the ARIMA (3, 1, 1) model will be used in our future investigation.

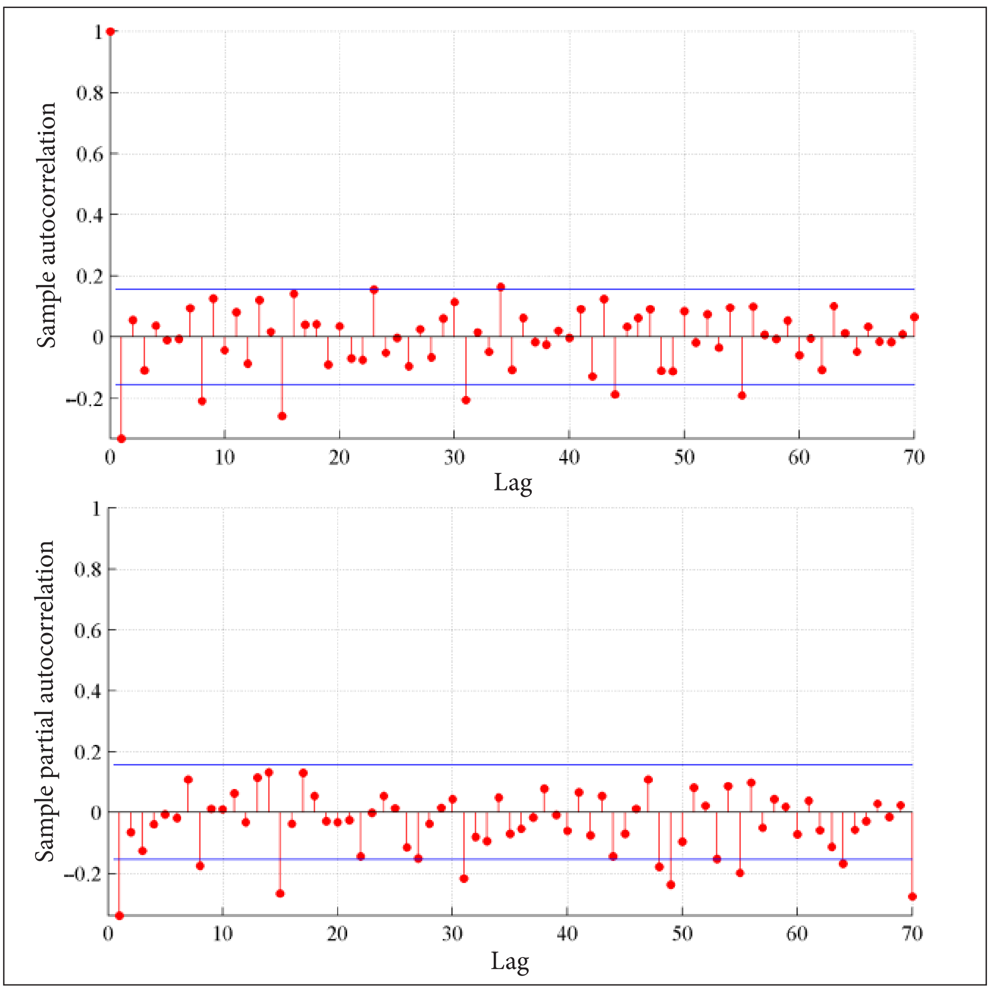

Fig. 2. Autocorrelation and partial autocorrelation functions for integrated wind speed data

Table 1. **RMSE values for different combinations of orders AR (*p*) and MA (*q*)**

Order of MA (q)	Order of AR (p)										
	0	1	2	3	4	5	6	7	8	9	10
0	3.5319	3.5025	3.4828	3.4880	3.4869	3.4865	3.4894	3.4899	3.5279	3.6654	3.6805
1	3.4683	3.6086	3.5118	3.4940	3.5014	4.9612	3.4573	3.9190	3.5665	3.6969	3.7742
2	3.5368	3.7164	3.5295	3.5053	5.0244	4.2038	3.5399	3.7605	3.7822	3.6981	3.7343
3	3.4905	3.6387	5.9987	4.2485	3.7341	6.2775	3.6042	3.9101	3.7334	3.7775	3.7167
4	3.4753	3.6843	5.9917	3.5986	3.5823	3.6008	3.6971	3.6698	3.7132	3.7595	3.9789
5	3.4858	3.6911	3.5148	3.9614	3.5713	9.1360	3.5445	4.7323	3.9738	3.7404	4.2609
6	3.4802	3.7208	3.4879	3.5412	4.0254	3.5713	3.6667	4.5943	3.9451	3.9657	5.0348
7	3.5313	3.6969	3.7632	3.5730	3.6913	3.6239	3.8356	3.7892	4.7330	5.7076	4.2781
8	3.5089	3.6586	4.0272	3.5185	3.7762	3.6557	3.9832	3.6770	3.9534	3.8107	4.0797
9	3.4451	3.6902	4.1143	3.5169	4.1921	3.6064	3.6666	3.6022	3.8641	4.5072	4.0205
10	3.4849	3.6442	5.3861	3.5357	3.6003	3.6781	3.6372	3.7121	3.8564	4.4965	4.0848

Forecasting

Using the ARIMA (3, 1, 1) model, further calculations were made. Each hour, the wind speed forecasts were made for the next 24 hours ahead. That was repeated for 168 data points (7 days).

To analyse 24 hours ahead actual and predicted values, the RMSE, MAE and MAPE criteria were used. The forecasting performance in three different input periods is revealed in Table 2.

Different forecast errors are shown after 2, 6, 12 and 24 hours. When the ARIMA (3, 1, 1) model is selected, the input data period should be analysed. Figures 3–5 show the main results of analysed input periods. Errors made from the beginning until the end of the day can reach 32% of the worst accuracy of forecast values, especially in the first analysed period.

As mentioned before, to find the best model structure and input periods, the MAE, RMSE and MAPE were used. Each error shows different changes in analysed data. All errors are shown in Figs. 3–5.

It is obvious that the third period causes the highest RMSE errors in Fig. 4, at least in the first 12 hours, and the second input period is the best. Furthermore, in the first two hours, the prediction with the first input period is even better than with the second one, but errors are higher in the further hours.

Figures 3 and 4 show that RMSE and MAE errors have very similar results. The training period was carried out for the prediction of 24 hours ahead. The 24-hour actual and predicted wind speed values of Figs. 3 and 4 were analysed: to 8 hours ahead and to 24 hours ahead. The difference in error value was the lowest between I and II input periods in the beginning of the forecasted 8 hours ahead. However, for 24-hour wind speed prediction, we received the lowest RMSE and MAE errors when the model was trained

Table 2. **RMSE, MAE, MAPE for 3 analysed input periods**

Time, h	RMSE			MAE			MAPE		
	I period	II period	III period	I period	II period	III period	I period	II period	III period
2	1.6045	1.6227	1.7844	1.2120	1.2293	1.3604	0.3565	0.3616	0.4001
6	2.6658	2.6627	2.8898	2.0351	2.0100	2.1873	0.3037	0.3000	0.3265
12	3.5827	3.4922	3.6184	2.8189	2.7533	2.8274	0.5998	0.5858	0.6016
24	5.0010	4.8617	4.9910	4.1110	3.9659	4.1451	1.0027	0.9673	1.0110

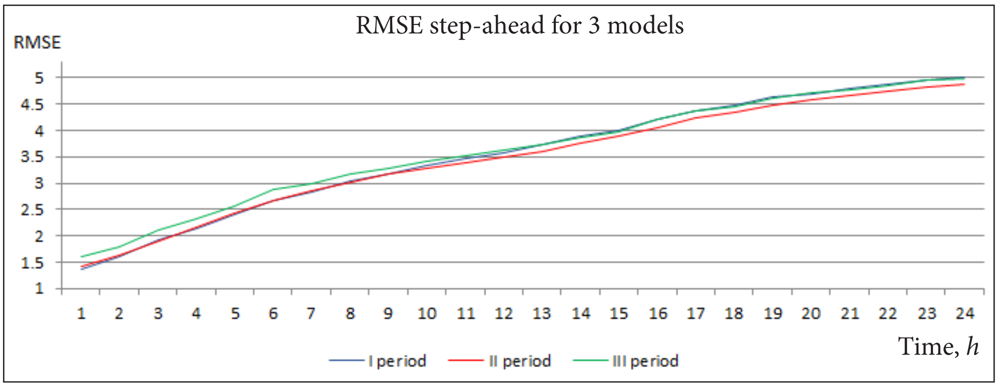

Fig. 3. RMSE every step-ahead for 3 input periods

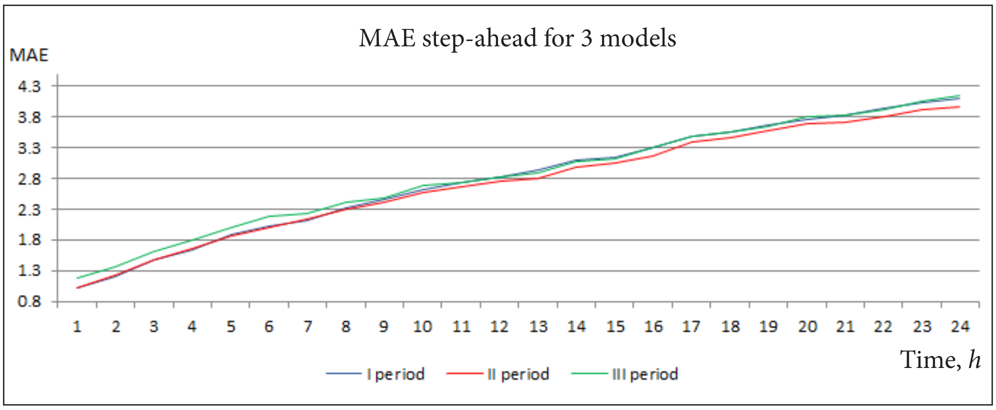

Fig. 4. MAE every step-ahead for 3 input periods

with the II input period. This indicates that the data from 18–31 January 2012 should be used in the ARIMA (3, 1, 1) model for winter season wind speed prediction. Also, this analysis has displayed that it is appropriate to use the ARIMA model for wind speed prediction for less than 6–8 hours ahead. Then the training period choice can be from two weeks to one month, and errors will be 1% close between.

The MAPE values are different from MAE and RMSE because the analysed wind speed data is unstable. However, it should be noted that MAPE is not the best measurement criterion to be used for the wind speed analysis, because some of wind speed data values are equal or close to 0 m/s. That is why it is better to use RMSE and MAE instead of MAPE to verify if the model is suitable for wind speed prediction, Fig. 5.

Figure 6 shows wind speed actual data and forecast values. To see the difference of day ahead prediction for all day long, we looked for wind speed forecast 2, 6, 12 and 24 hours ahead. The summarized results showed that inaccuracy of wind speed prediction 2 hours ahead was 8.5%, 6 hours ahead 17.5%, 12 hours ahead 28.9%, and 24-hour prediction reached 42.4% of actual data. It can be confidently stated that a longer period of wind speed prediction causes higher errors. In addition, wind speed prediction becomes increasingly inaccurate after a long time period. Figure 3 shows that ARIMA forecast quality depends on invariability of the data. When there are sudden changes in the analysed data, higher errors occur. The reason behind this is the use of previous wind speed values in ARIMA model prediction. The bias could be seen in Fig. 6. The higher values of parameters p and q lead to inaccurate results because the prediction function becomes linear.

Model suitability verification

Previous investigation covered data from the winter season only. However, it is beneficial to know

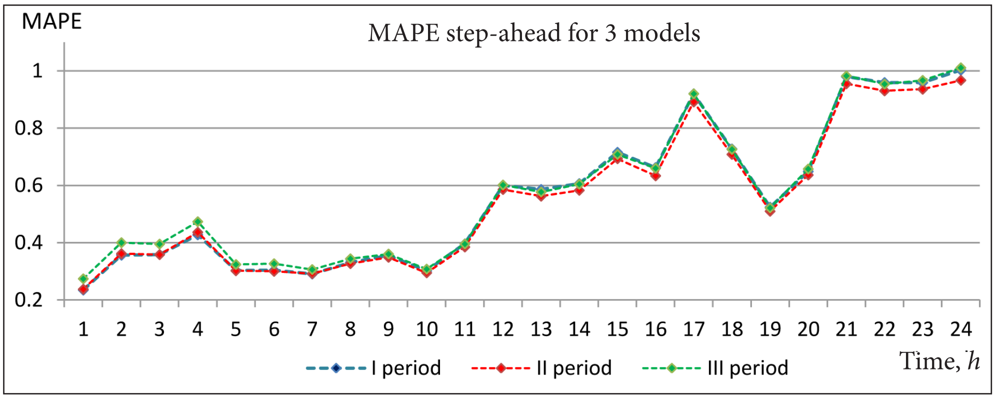

Fig. 5. MAPE every step-ahead for 3 input periods

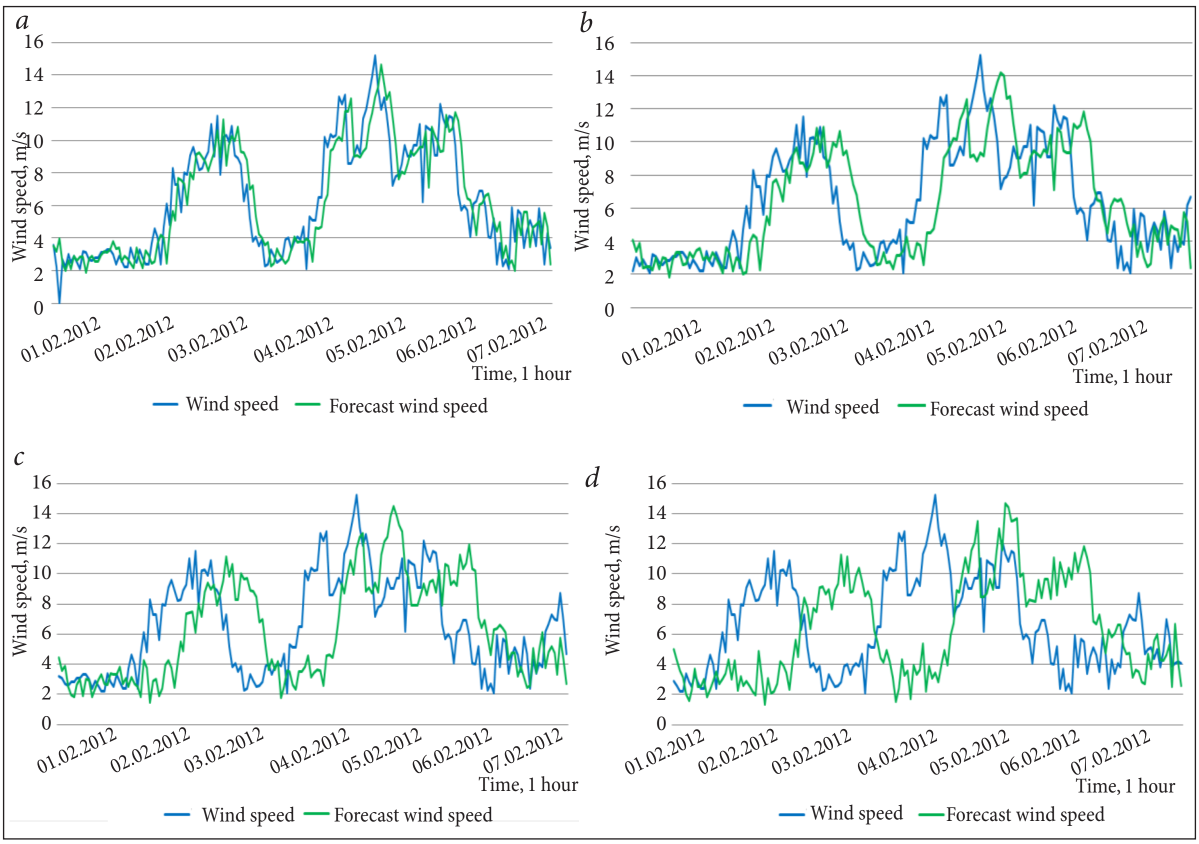

Fig. 6. (a) 2 hours ahead, (b) 6 hours ahead, (c) 12 hours ahead, and (d) 24 hours ahead real and forecast wind speed

if the same model is able to predict wind speed in other seasons. Further investigation contains wind speed data of the winter, spring, summer and autumn seasons of the year 2012, results are shown in Figs. 7–9.

Figures 7 and 8 show that RMSE and MAE depend on the season. The model predicts winter, summer and autumn with similar error values. The worst error values were found in the prediction of the spring season. The 12-hour ahead forecasts of the winter season appeared to be similar to summer and autumn forecasts, while spring prediction was more rough than winter values, differing by approx. 1 m/s in terms of MAE.

Very similar results can be seen in Fig. 8; where the predicted values of the winter period in the end of the day are high and reach almost

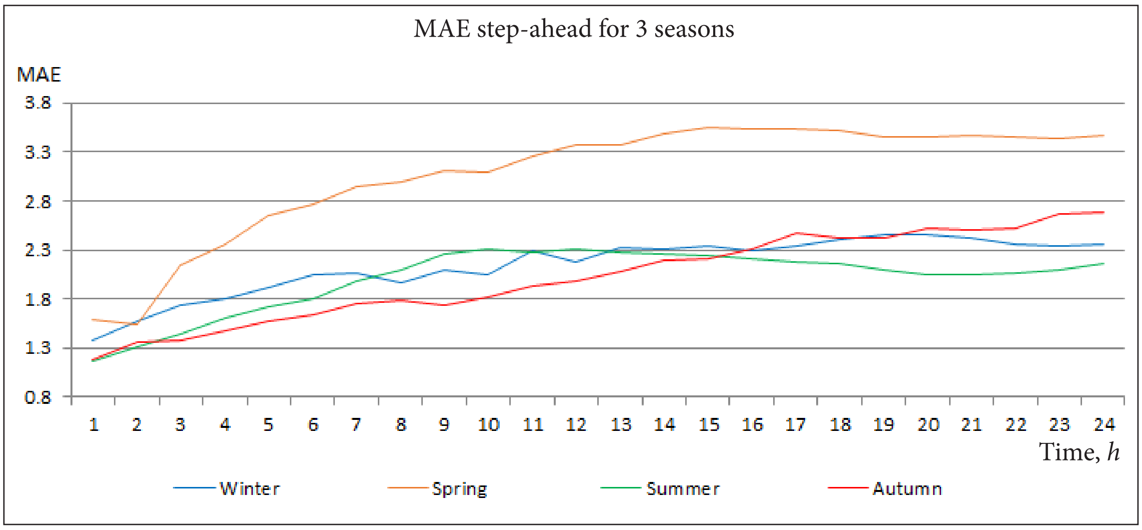

Fig. 7. MAE every step-ahead for 4 seasons

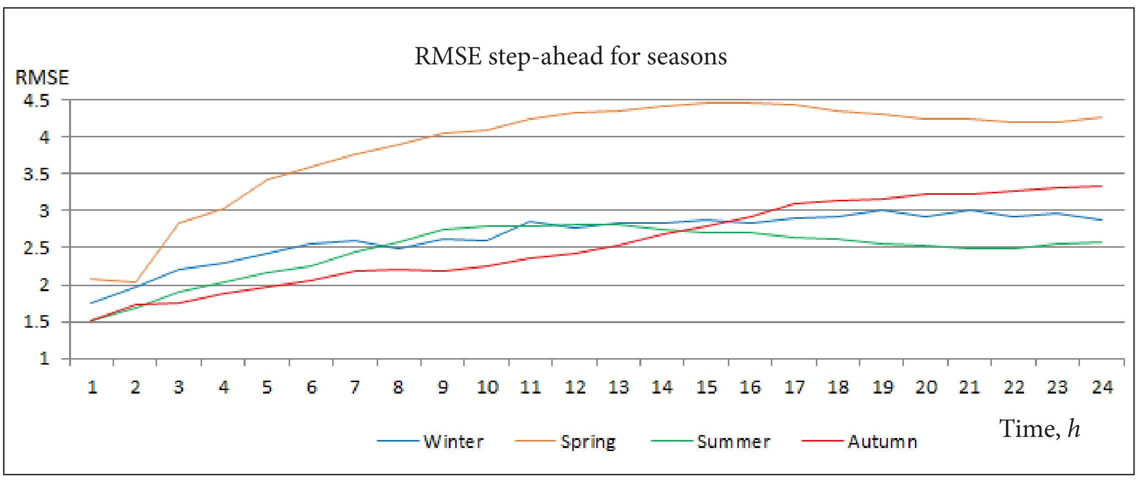

Fig. 8. RMSE every step-ahead for 4 seasons

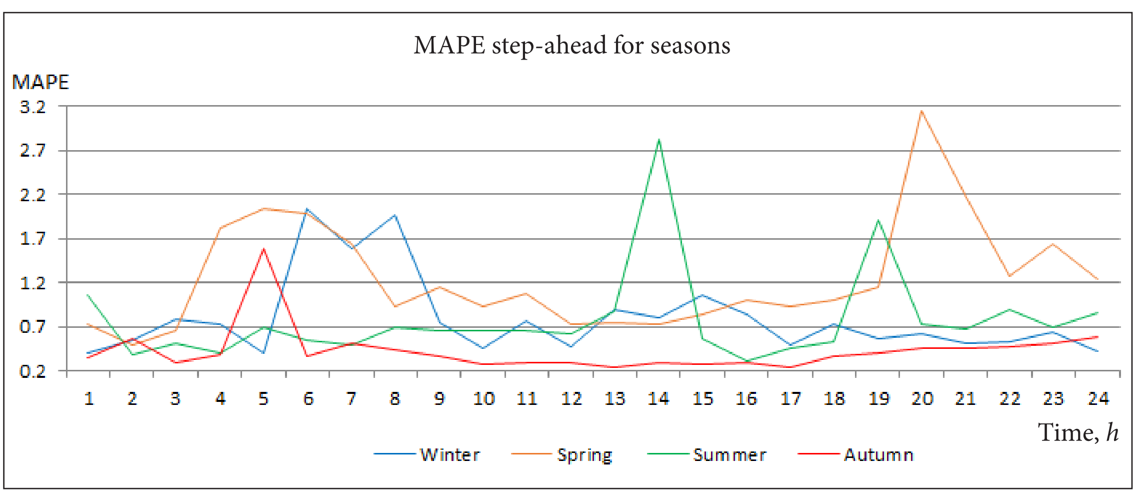

Fig. 9. MAPE every step-ahead for 4 seasons

2.5 m/s, but, as can be observed, spring period is by 43% worse in inaccuracy.

This could be caused by small data variations. In the year of 2012, the spring season was particularly windy with sudden changes in wind speed. However, it is clear that the model ARIMA (3, 1, 1) is not good enough for the spring data prediction. This analysis has shown that finding a single ARIMA model for all the seasons is not enough, and additional structure research needs to be made for the spring season.

A comparison of MAPE errors in all seasons is shown in Fig. 9.

As it is seen in Fig. 9, the MAPE errors vary in different seasons. The sudden jumps in errors show that wind speed at the jump time was most likely equal or close to 0 m/s. Furthermore, this may also present the instability of the wind speed data. The smallest MAPE errors are seen in the autumn season. This shows a small variation in the wind speed data. It was mentioned before that MAPE errors sometimes are not very appropriate to be used in wind speed prediction, because MAPE may not show the tendency of wind speed stability in seasons.

However, this investigation also shows that more characteristic errors in this analysis are RMSE and MAE.

CONCLUSIONS

This study has shown that the best ARIMA structure (p, d, q) to forecast the wind speed for the selected Baltic region locality is (3, 1, 1). This structure can be used in summer, winter and, in particular, autumn seasons, while it should be changed for the spring season because of sudden changes in wind speed data.

Analysis of three different retrospective data periods revealed the fact that a two-week interval has the lowest prediction error rates in comparison with one month and a 3-day period. It is recommended to use the ARIMA (3, 1, 1) model to forecast wind speed for the first 6–8 hours, because the accuracy of the method is lower when it is used for longer periods of time.

We suggest to choose RMSE and MAE for wind speed analysis and structure selection. MAPE is good in forecasting wind power, but less suitable for wind speeds.

To reduce errors obtained, the use of a hybrid model (ARIMA combined with other techniques) should be addressed.

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TRUMPALAIKĖ VĖJO GREIČIO PROGNOZĖ NAUDOJANT ARIMA MODELĮ

Santrauka

Masinė vėjo energijos integracija į elektros energetikos sistemas skatina gerinti trumpalaikes vėjo greičio prognozes. Tai padeda perdavimo sistemos operatoriui lengviau balansuoti sistemą ir mažinti rezervinės galios, reikalingos vėjo generacijos svyravimams kompensuoti, poreikį. Vėjo greičiams prognozuoti dažnai yra taikomi statistiniai laiko eilučių metodai. Laiko eilutės yra apibrėžiamos kaip chronologinė nagrinėjamo parametro reikšmių seka. Šiame straipsnyje analizuojamas statistinis vėjo greičių trumpo prognozuojamo laikotarpio (iki 24 val.) modelis ARIMA (autoregresinio integruoto slenkančio vidurkio modelis). Laiko eilučių analizėje ARIMA modelio tikslumas priklauso nuo prognozuojamo vidurkio. Jis remiasi prognozuojamų vėjo greičio duomenų priklausomybe nuo praeities reikšmių. ARIMA modelis yra taikytas įvairiems prognozavimo uždaviniams spręsti, įskaitant ir trumpalaikes vėjo greičių prognozes. Jis paprastai laikomas ankstyvuoju laiko eilučių metodu, kurio ribotumas – nepakankamas vėjo greičių prognozių tikslumas antroje prognozavimo paros pusėje. Laikotarpiui ilgėjant, prognozės gaunamos su didėjančiomis paklaidomis. Pagrindiniai darbo tikslai: 1) rasti optimalios struktūros ARIMA modelį (praeities duomenų laikotarpį ir eiles p, d, q); 2) patikrinti, kiek pagal tikslumo kriterijus yra priimtinas tos pačios struktūros ARIMA modelis prognozuojant skirtingiems metų sezonams (pavasariui, vasarai, rudeniui ir žiemai). Tikslumas vertintas vidutinės kvadratinės paklaidos (RMSE), vidutinės absoliutinės procentinės paklaidos (MAPE) ir vidutinės absoliutinės paklaidos (MAE) kriterijais. Ieškant optimalių eilių p (autoregresijos AR) ir q (slenkamojo vidurkio MA), naudotos autokoreliacijos (ACF) ir dalinės autokoreliacijos (PACF) funkcijos. Laiko eilutės duomenys buvo imami iš realių matavimų, užfiksuotų vienoje Baltijos regione esančioje vietovėje. Skaičiavimai leido rasti optimalią modelio struktūrą, kuri yra pakankamai tiksli 6 val. prognozavimo laikotarpiui, tačiau visiems metų sezonams tos pačios struktūros modelį naudoti nerekomenduotina. Remiantis gautais rezultatais, siūlome šį modelį ateityje naudoti kaip pagalbinį hibridiniame modelyje su kitu efektyvesniu metodu.

Raktažodžiai: ARIMA, elektros energijos sistema, vėjo greitis, trumpalaikė prognozė