Scientific quarterly journal ISNN 1429-7264

Agricultural Engineering

2014: 4(152):81-90

Homepage: http://ir.ptir.org

DOI: http://dx.medra.org/10.14654/ir.2014.152.083

COMPARATIVE ANALYSIS OF WIND SPEED SHORT TERM FORECASTS FOR WIND FARMS

Małgorzata Jaros*, Piotr Obidziński

Department of Foundamentals Engineering, University of Life Sciences in Warsaw

*Contact details: ul. Nowoursynowska 164, 02-787 Warszawa, e-mail: malgorzata_jaros@sggw.pl

ARTICLE INFO

Article history:
Received: August 2014
Received in the revised form: September 2014
Accepted: October 2014

Keywords:
forecasting
wind speed
wind farm

ABSTRACT

The purpose of study was verification regarding quality of wind speed forecasts used during designing the wind farm capacity, with AAN [artificial neural network] methods and Brown, Holt, Winters and ARIMA time models. Analysis included results of forecasts for December, namely a month with the biggest wind speed amplitude changes, considering data for period of 2008-2009. Analysis of results confirmed that appropriate linear models and artificial neural methods for the period of wind speed forecast may ensure good results regarding forecasts of wind power output generated by wind farms.

Introduction

Wind power industry in Poland is more and more popular, and technology used for wind power generation undergoes quick development. Wind power is environmentally friendly, and features easy operation, small costs and relatively small negative impact, although lately lively public debates have followed regarding this last issue. Areas which until now were considered unfavourable for wind farms due to wind conditions, at present have been purposed for operation. Well designed wind farms at present technology development enable to achieve many economical benefits. Yet forecast regarding energy generated by wind farms actually constitutes a big problem, and therefore more interest is focused on the methods for wind farm capacity forecast preparation. The wind speed is the main parameter that has impact on the wind farm capacity. Any error during wind speed assessment in consequence results in discrepancy of forecasted and actual energy generated by a wind farm. Actually, it results from the fact that the wind farm power is proportional to the cubed wind speed. The Energy Law Act determines the framework for the electric energy market differently than for other energy sources and the precise principles regarding reporting the wind farm operation plan, laid down in the Transmission System Operation and Maintenance, the balancing mechanism for electric energy sources, enables the correction for planned electric energy delivery to the grid, not later than 2 hours before hourly period of generation thereof. Therefore, ultra-short time forecasts covering the period of few hours are the most crucial for the electricity system operation (Karkoszka, 2010).

The objective and scope of research

The characteristic feature of a wind farm relates to varied operation conditions, resulting from wind speed variations. Highly variable electricity generated by a single wind farm may pose a threat to the electricity system. Therefore, owners of wind farms were obliged to prepare estimates regarding generated energy. Thus, the purpose of the study was to verify whether artificial neural networks, and selected linear mathematical models may provide an effective tool for wind speed forecasting.

Characteristics of measuring data

Data used for preparation of forecasts included measuring data of wind speed, air temperature and atmospheric pressure, recorded every hour, as of 2008-2009, at weather station close to Żelazna near Skierniewice, collected by Electricity Management Plant SGGW. Wind speed, V, measurements were made with the h_{data}=12 m high mast. Speed readings were converted into values corresponding to height where wind farm generators were installed, and these values were specified later on, in the paper, namely h=73 m, with application of formula (Scire et al., 2000; Szczygłowski, 2007):

$$V_h = V_{h_{data}} \left(\frac{h}{h_{data}}\right)^{0.26} \qquad (1)$$

The power factor (of area roughness) was determined empirically for the location where the measuring data were collected. Figure 1 presents diagram regarding daily distribution of mean wind speed values recorded every hour, specified for the analyzed period. The distribution was similar to the normal one, with displacement by vector 5.8 m·s^{-1} and of the mean value obtained during midday.

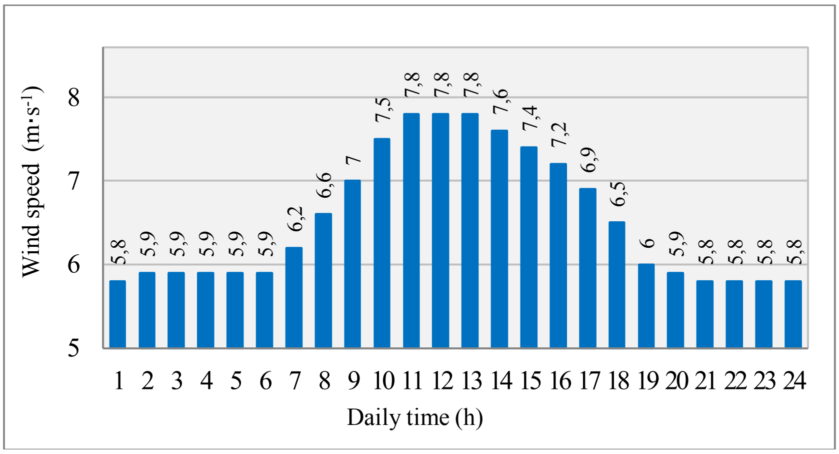

Figure 1. Distribution of average hourly wind speeds, in the period 2008 and 2009

Wind speeds at particular months of different years that may differ significantly, which was the case in 2008 and 2009, and Figure 2 presents their daily mean values for subsequent months of these years.

Diagram in Figure 2 confirms the strongest wind identified in the late autumn and winter. The average annual wind speed determined for the data obtained at the weather station at Żelazna, at height 73m was 6.52 m·s^{-1}.

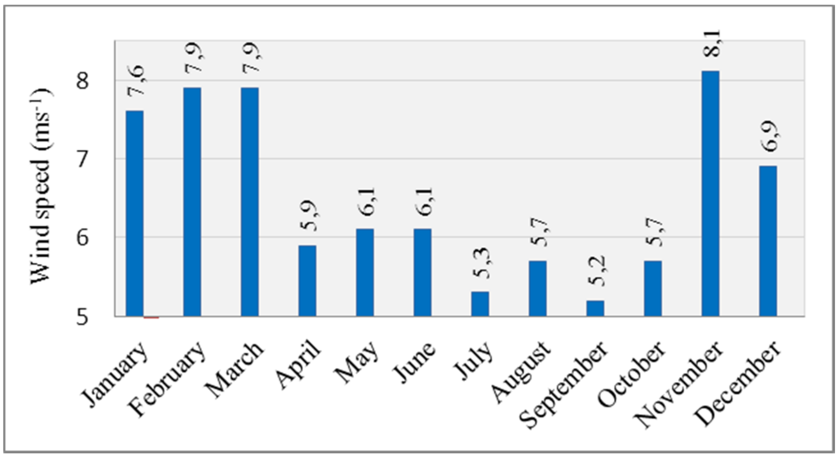

Figure 2. Distribution of mean monthly wind speeds, on the basis of accumulated data from the period of 2008 and 2009

For more precise assessment regarding usefulness of forecasting models, results of forecasts were considered for December, a moth that features biggest sudden amplitudes, which made forecasting more difficult.

All forecasts have been prepared with Statistica software.

Forecasts based on the artificial neural networks (AAN)

Assessment regarding fitness of SSN for preparing wind speed forecasts was based on the basis of comparative analysis of forecasts in advance of 1, 3, 6, 12 and 24 hours. Forecasts were prepared with use of MLP multi-layer perception. Input data set included:

- information on the date of measurement, namely year, month, hour,
- wind speed according to historical data, and its 24 preceding values,
- air temperature according to historical data, and its 24 preceding values,
- atmospheric pressure according to historical data, and its 24 preceding values,
- information on sudden changes of pressure and temperature within a single hour.

Hidden neurons of forecast taking into account pressure and temperature were activated on the basis of exponential function, whereas an output neuron was activated by sine function. In case of a forecast that was not based on other input data except of wind speed, hidden neurons action was based on logistics function whereas output neuron was activated with exponential function.

Verification confirmed that the historical data on the wind speed is crucial for the quality of a forecast, whereas other information namely on temperature and pressure had little impact on the forecast quality. Table 1 presents reference historical data for two neural models that provided best forecasts 1 hour in advance.

Table 1
Assessment of neuron models providing forecasts 1 hour in advance

Model	Output data		MAE	RMSE	Coefficient factor
MLP 111-8-1	Speed, Pressure, Temperature	Learning	1.14	1.52	0.90
		Validation	1.16	1.57	0.87
		Test	1.31	1.71	0.89
MLP 60-18-1	Speed	Learning	1.16	1.55	0.90
		Validation	1.18	1.58	0.86
		Test	1.34	1.76	0.88

Diagrams regarding wind speed included in the following drawings relate to the period of 12 days, whereas the horizontal axis determines the beginning of each next day (0h) and afternoon (12h). Figure 3 includes a comparative analysis regarding results of forecasts for 3, 6 and 12 hours in advance against actual values of wind speed.

According to neuron calculations, for forecasts specified on 3 Figure, increase of time resulted in bigger errors of forecasts. Additionally to deviations' increase from measured values, it was evident that values of wind speed forecasts were close to mean value of this speed.

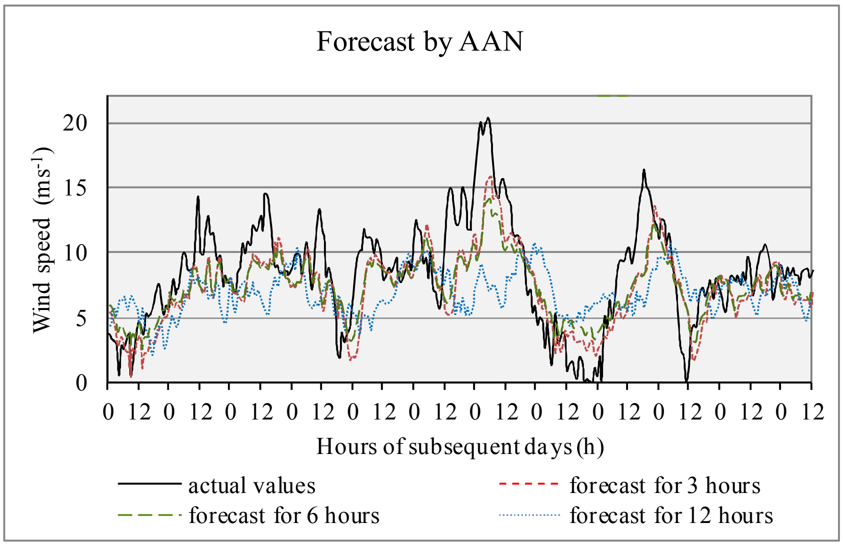

Figure 3. Diagrams of neuron model forecasts 3, 6 and 12 hours in advance, based on input data including historical data of wind speed, atmospheric pressure, air temperature and date of measurement

Forecasts based on time models

The typical models forecasting the value changing depending on variations, were the models of time series. The study verified application of Brown's, Holt's, Winters' and ARIMA models for wind speed forecasting:

Brown's model finds application, when variability of the forecasted variable is almost constant, no development follows within time series, and fluctuations of value resulted from impact of random factors (Cieślak, 2011). The forecast was determined on basis of the following formula (2):

$$y_t^{*} = \propto y_{t-1} + (1-\propto) y_{t-1}^{*} \tag{2}$$

where:
y_{t-1}^{*} – value forecasted at a given value of the smoothing factor,
y_t^{*} – forecast of Y variable value determined for t time,
$\propto$ – smoothing factor, of values from range (0,1],

According to Brown's model, the forecast for 1 period in advance was the combination of model actual past value, and forecast past value. The smoothing factor was determined on the level of 0.95. Figure 4 presents Brown's model diagram forecasting wind speed 1 hour in advance:

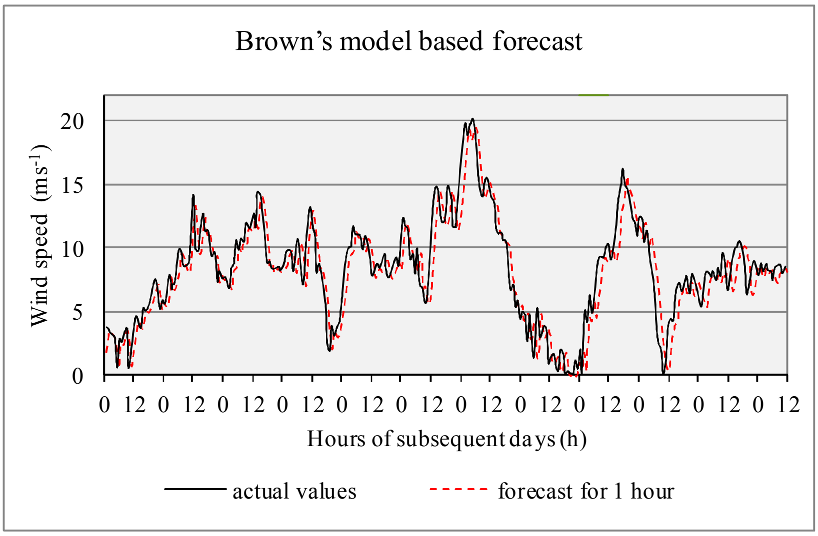

Figure 4. Brown's model based forecast, 1 hour in advance

Although simple, Brown's model works better than artificial neural networks. Table 2 presents the errors of models that help to assess the quality of forecasts.

Holt's model has been applied for forecasting phenomenon when accidental fluctuations follow and evident development trend (Halicka and Winkowski, 2013). In theory, this model featured more flexibility comparing to Brown's model, as it had two smoothing factors. Holt's linear model based on (3) and (4) equations and forecast (Cieślak, 2011) was determined with the following formula (5):

$$F_{t-1} = \propto \cdot y_{t-1} + (1-\alpha)(F_{t-2} + S_{t-2}) \tag{3}$$

$$S_{t-1} = \beta(F_{t-1} - F_{t-2}) + (1-\beta)S_{t-2} \tag{4}$$

$$y_t{}^{*} = F_n + (t-n)S_n \ , \tag{5}$$

where:

F_{t-1}, (F_n) – smoothed variable value forecasted for time t-1, (n),
S_{t-1}, (S_n) – smoothed value corresponding to trend gain for time t-1, (n),
n – number of value within time series,
α, β – smoothing parameters within range (0,1].

Smoothing parameters determined in the work: α=0.95, β=0.05 provided better results. Forecast based on Holt's model 1 hour in advance provided forecasts comparable to ones based on Brown's model. Observing wind speeds hour after hour, development tendency was evident that followed most often from 3 to 4 hours. Figure 5 presents forecast diagram 3 hours in advance.

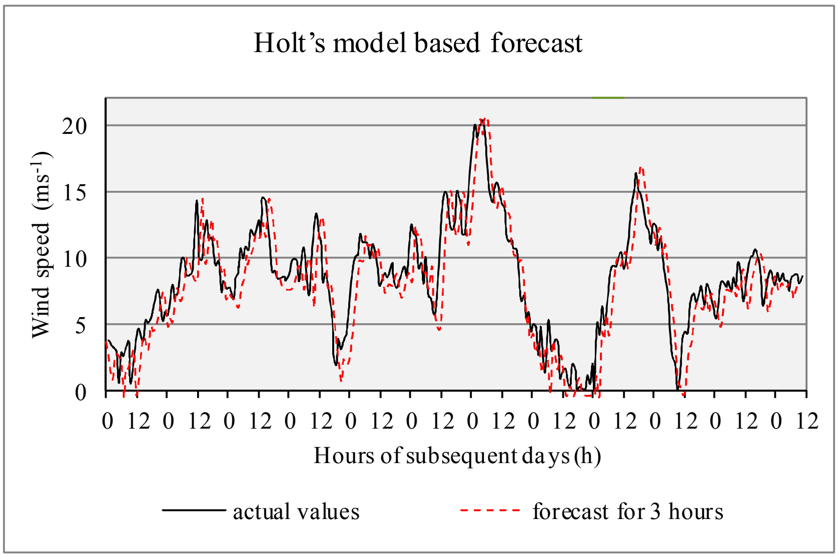

Figure 5. Holt's model based forecast, 3 hours in advance

The diagram demonstrated evident displacement with reference to actual values, so delay of forecast was evident. Comparative analysis of Holt's models and artificial neural networks, 3 hours in advance or more indicated that neural based model was more precise.

Winters' additive model is preferred, when the seasonal variations, development trend and accidental variations follow through the series time. Winters' additive model (Karkoszka, 2010) was based on (6)-(8) formulas and forecast computation was based on (9) formula.

$$F_{t-1} = \propto (y_{t-1} - C_{t-1-r}) + (1\text{-}\propto) * (F_{t-2} + S_{t-2}) \tag{6}$$

$$S_{t-1} = \beta(F_{t-1} - F_{t-2}) + (1 - \beta) * S_{t-2} \tag{7}$$

$$C_{t-1} = \gamma(y_{t-1} - F_{t-1}) + (1 - \gamma)C_{t-1-r} \tag{8}$$

$$y_t{}^* = F_n + S_n(t - n) + C_{t-r} \tag{9}$$

where:

$F_{t\text{-}1}$ – smoothed variable value forecasted for time t-1,
$C_{t\text{-}1}$ – smoothed seasonality value for time t-1,
$S_{t\text{-}1}$ – smoothed value corresponding to trend gain for time t-1,
r – total seasonal cycle length,
α, β, γ – smoothing parameters within range (0,1].

For the needs of Winters' additive model and purpose of this forecast, the following parameters: $\alpha = 0.95$, $\beta = 0.05$, $\gamma = 0.05$ were applied. For example, Figure 6 presents the results of forecast 1 in advance. The forecast results were similar to the results obtained with Holt's model. Winters' model demonstrated slightly more advantageous MAE average absolute error and average-square error elements for these models were almost the same. Almost identical relation follows when comparing errors of forecast 3 hour in advance. It testified to similar limited usefulness of both Winters' and Holt's model for the wind speed forecasts a few hours in advance.

Results of forecasts were similar to those based on Holt's model. Winters' model demonstrated slightly more advantageous MAE average absolute error and average-square error elements for these models were almost the same. Almost the same dependency was evident when comparing errors of forecasts 3 hours in advance. It proves similar limited usefulness of both Winters' and Holt's model for the wind speed forecasts a few hours in advance.

As Brown's model worked better comparing to Holt's model, verification also followed regarding Winters' model excluding development trend, by applying appropriate corrections to equations – smoothed trend gain calculation was excluded. Forecast 1, 3 and 6 hour in advance underwent verification. The model excluding development trend provided better forecast 1 and 3 hours in advance, whereas time over 3 hours in case of Winters' model indicated its poor quality comparing to the neural method, what was also confirmed with error comparative analysis included in table 2.

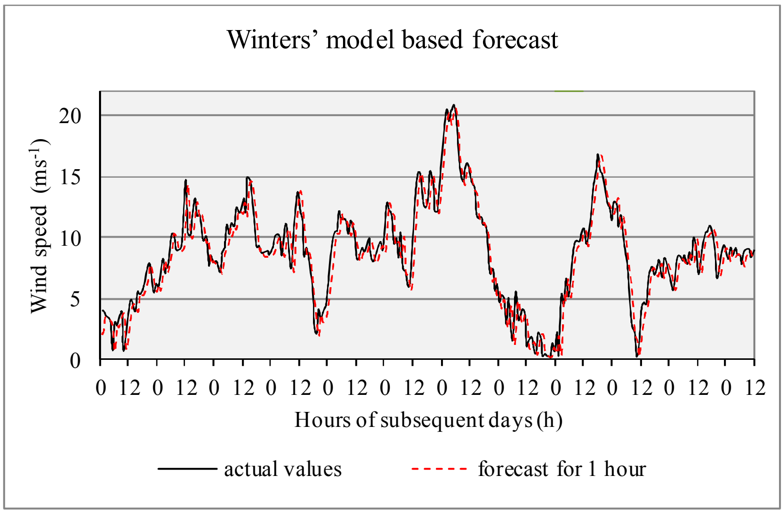

Figure 6. Winters' additive model based forecast 1 hour in advance

ARMA/ARIMA models considered as ones of the best methods for forecasting of time series. Application thereof for forecasting includes use at least 60 observations, what in this case was not a problem, due to a large set of the possessed data. ARIMA model was a combination of auto-regression and moving average structure models. Forecast was prepared (*ARMA and ARIMA models in*: Econometrics. Forecasting and simulations; StatSoft, 2006) using the following formula:

$$y_t = \Phi_0 + \Phi_1 y_{t-1} + \ldots + \Phi_p y_{t-p} + e_t - \Theta_1 e_{t-1} - \ldots - \Theta_q e_{t-q} \tag{10}$$

where:

$\Phi_0, \Phi_1, \ldots \Phi_p, \Theta_0, \Theta_1, \ldots \Theta_q$ – model factors,

p, q – delay;

e_t, e_{t-1}, e_{t-2} – model remaining for time t, t-1, t-q.

ARIMA model (p,d,q)(P,D,Q), taking into account seasonality demonstrated the smallest errors when forecasting wind speed 1 hour in advance, and Table No. 3 includes errors of this forecast. The obtained model including seasonality of wind forecast 1 hour in advance was as follows: ARIMA(2,0,1)(2,0,1), which in brief was ARMA(2,1)(2,1). The analyzed study the model was applied with p=2 two auto-regression parameters and q=1 moving average one parameter, as well as, in this case, model did not require differentiation, d=0. Forecasting precision with this method in case of long time, similarly to neural networks resulted in large errors also.

Summary and conclusions

The purpose for application of data regarding December, namely a month that features big speeds and sudden wind speed variations was verification regarding quality of forecasts at the most unstable conditions. In case of summer months, the analyzed forecasts demonstrated smaller errors than correlation coefficient, and bigger for models generated with the neural methods. The Table 3 includes summary namely values of errors for all tested forecasting methods.

Table 3
Statement of mean errors for considered forecast models

ANN (MLP)

Forecast time	1h (wind only)	1h	3h	6h	12h	24h
MAE	1.34	1.31	1.68	1.97	2.28	2.54
RMSE	1.76	1.71	2.18	2.56	3.05	3.28

Time series models (linear)

Forecast time	Brown's	Holt's		Winters'				ARIMA
				With trend	Without trend			
	1h	1h	3h	1h	1h	3h	6h	1h
MAE	0.9	0.92	1.69	0.91	0.90	1.59	2.22	0.87
RMSE	1.23	1.25	2.28	1.25	1.23	2.14	2.93	1.19

The results of research provided grounds for the following conclusions:

1. The best results for forecast 1 hour in advance, with smallest MAE absolute mean error and RMSA average-square error obtained ARIMA model, good results obtained also Winters' model without trend and Brown's model, whereas poor results below the mentioned ones obtained neural models.
2. Brown's model was ineffective for longer periods.
3. In case of forecasts 3 hours in advance, ARIMA or Winters' models without trend may be used also.
4. Linear models described in this paper demonstrated big errors when forecasting wind speed 6 hours in advance and more.
5. Applying wind speed data as input data on wind speed neural models from preceding periods and additionally current air temperature and atmospheric pressure provides for quality improvement of forecast prepared with this method.

According to this study, the general recommendation is evident that a combined model can be an effective way to provide a reliable wind speed forecast prepared 24h in advance or more.

References

Bielak, J. (2010). *Prognozowanie rynku pracy woj. lubelskiego z wykorzystaniem modeli ARIMA i ARIMAX.* Wyższa Szkoła Zarządzania i Administracji w Zamościu, 28-30.

Cieślak, M. (2005). *Prognozowanie gospodarcze. Metody i zastosowania.* Wydawnictwo naukowe PWN, Warszawa, 69-75.

Halicka, K.; Winkowski, C. (2013). *Wykorzystanie metod wygładzania wykładniczego do prognozowania kursu sprzedaży EURO.* Politechnika Białostocka, 71-76.

Karkoszka, K. (2010). *Metody prognozowania wielkości mocy elektrycznej z farm wiatrowych dla potrzeb bilansowania oraz prowadzenia ruchu krajowego systemu elektroenergetycznego.* IGSMiE PAN, 77-83.

Kowalski, L. (2005). *Prognozowanie i symulacje. Model Browna.* Pozyskano z: http://pis.rezolwenta .eu.org/Materialy/Model-Browna.pdf.

Scire, J.S.; Robe, F.R.; Fernau, M.E.; Yamartino, R.J. (2000). *A User's Guide for the CALMET Meteorological Model (Version 5).* Earth Tech, Inc., Concord. Pozyskano z: http://www.src.com/calpuff/download/CALMET_UsersGuide.pdf, dostęp wrzesień 2013

StatSoft (2006). *Analiza szeregów czasowych.* Elektroniczny Podręcznik Statystyki . PL, Krakow, WEB: http://www.statsoft.pl/textbook/stathome.html.

Szczygłowski, P. (2007). *Ocena przydatności wybranych modeli gaussowskich w obliczeniach stanu zanieczyszczenia powietrza. Rozprawa doktorska,* AGH, Wydział Geodezji Górniczej i Inżynierii Środowiska. Maszynopis.

Ustawa z 10 kwietnia 1997r. Prawo energetyczne. Dz.U. z 2006 r. Nr 89, poz. 625 ze zm.

Instrukcja ruchu i eksploatacji sieci przesyłowej. Warunki korzystania, prowadzenia ruchu, eksploatacji i planowania rozwoju sieci. Tekst jednolity zatwierdzony decyzją Prezesa URE nr DPK - 4320-1(2)/2011/LK z dnia 28 czerwca 2011r.

Modele ARMA i ARIMA. Ekonometria. Prognozowanie i symulacje-Pomoc. Pozyskano z: *Ekonometria.4me.pl/modele-arma-arima.htm.*

PORÓWNANIE MODELI KRÓTKOOKRESOWYCH PROGNOZ PRĘDKOŚCI WIATRU DLA SIŁOWNI WIATROWYCH

Streszczenie. Celem pracy było sprawdzenie jakości prognozy prędkości wiatru, wykorzystywanej w planowaniu mocy siłowni wiatrowej, metodami SSN i modelami szeregów czasowych Browna, Holta, Wintersa i ARIMA. Porównano wyniki prognoz sporządzonych dla grudnia, miesiąca o największych zmianach amplitudy prędkości wiatru, sprawdzając je dla danych z lat 2008-2009. Analiza wyników wskazuje, że odpowiedni dobór modeli liniowych i sztucznych sieci neuronowych do horyzontu czasowego prognozy prędkości wiatru, może pozwolić na osiągnięcie dobrych wyników prognozowania energii, wytworzonej przez siłownie wiatrowe.

Słowa kluczowe: prognozowanie, prędkość wiatru, siłownia wiatrowa