Comparative analysis of the renewable energy generation forecasts in Poland and Portugal and their influence on the energy exchange prices

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Abstract

The share of the renewable energy and in particular the raising contribution of wind resources in the national energy-mixes of European countries showed a rapid growth over the last decade. Simultaneously, the beginning of the 20^{th} century brought a revolution to the electricity trading systems, which from the state-owned structures transformed into free and competitive markets. Contemporarily, the privileged position of the wind energy producers is being weakened by their enforcement to participate in the market on equal terms, what entails the necessity of accurate production forecasting, what has been of secondary importance so far. The main aim of this study was to comparatively examine the wind generation forecasts in Poland and Portugal, as well as to verify their influence on the day-ahead market prices. The statistical analysis revealed significant deviations of the forecasted and actual wind production in both countries, which referred to the correspondent SPOT and balancing prices brought considerable financial losses from the perspective of energy suppliers. In the end, the influence of the wind generation forecasts on the SPOT prices has been examined by means of developed ARMA, ARMAX, NAR and NARX models. The results have shown that the usability of the information of forecasted wind generation is not unequivocal in developed SPOT prices models in Poland, mainly because of the randomness and volatility of recorded wind generation forecasts. However, in the case of Portugal, the forecasted wind generation occurred to be a valuable input in SPOT prices models, what has reflected in improved models accuracy.

Key words: Electricity Price Forecasting (EPF), Wind Power Forecasting (WPF), SPOT market, ARMA, ANN

1. Introduction

Sustainable development of contemporary power system in the direction of Renewable Energy Sources (RES) requires facing the problems with unpredictability of their availability at a given time, what crossed with the time-variation of the load in the system and volatility of energy prices on the wholesale markets makes this issue strongly elaborate. One of the key aspects of reliable functioning of the power system is proper planning of the supply versus demand, which in light of the RES generation uncertainty becomes a struggle for responsible entities. The inaccuracy of the e.g. wind generation forecasts entails consequences of two primary natures: (i) technical – divergence of the forecasted planned RES generation impedes the TSOs to properly and accurately plan the fulfilment of actual demand by available power capacity and (ii) economical – the uncertainty of the total forecasted wind power supply to the system translates into the uncertainty of the day-ahead and balancing market prices, what can result in financial losses of the market participants. The study being the subject of this paper will refer to the latter aspect.

1.1. Aims and objectives

In the literature, numerous publications can be found which support the hypothesis that the wind energy forecast is a valuable input in wholesale market price forecasting. Moreover, a wide range of mathematical models have been developed as well [2,3,4] – however, their universalism has not been tested on divergent market environments, such as Polish and Portuguese ones. The abovementioned concerns have led to the statement of several research problems which have been addressed by this project:

The quality of overall wind power forecasts in Poland and Portugal and the most-distinguishing features of the forecasting errors. Evaluation of the wind power prognoses will be made by means of statistical measures, which in quantitative way will give a picture on the accuracy, characteristics and tendencies observed.

The cost of inaccurate wind power forecasting globally from the perspective of wind power producers in both countries. Using the market and wind generation data available for both countries, a financial loss from inaccurate wind power predictions will be calculated, which will illustrate the range and importance of the appropriate and accurate wind generation forecasts.

Extent to which the information of expected wind generation improves the accuracy of the wholesale market prices forecasts in both examined countries. The verification of whether a wind generation has a value in predicting market prices requires developing mathematical models. For the purpose of the study, the four models commonly used in dealing with SPOT market prices time series have been developed (ARMA, ARMAX, NAR and NARX).

1.2. Outline

In order to introduce the reader to the context of the abovementioned problems, the state-of-the-art section has been devoted to the actual research recognition on the topics of wind power and SPOT market prices forecasting, together with particular focus on their interrelation. Further, a brief description of the methodologies applied in solving the research problems stated in the introduction, including the basic statistical measures for dealing with forecasting error analysis and fundamentals of time series models constructed in terms of this study has been prepared. In the next section, the study results will be presented, beginning from the statistical description of the wind generation forecasts error for Portugal and Poland and related potential penalties suffered by the wind power producer globally. Finally, the SPOT prices forecasting results will be presented for the developed time-series models, with their comparative evaluation. At the end of this paper, the most significant findings will be highlighted with the emphasis of the opportunities for future work on the topic.

2. State-of-the-art review

Contemporarily, when the electricity is traded on the wholesale markets, the uncertainty regarding the amount of wind energy supplied to the system influences directly the prices on the market. Every excess or deficiency of energy in the system has a consequence in the financial outcomes of energy suppliers/receivers [2]. This elaboration concerns the two crucial problems in sustaining modern power systems, being a subject of intensive research within last decades, which are the Wind Power Forecasting (WPF) and Electricity Price Forecasting (EPF). The increasing share of wind energy in the power systems, together with tendency for equalization of wind power producers with all the remaining electricity market participants leads to the enhancement of interaction between the WPF and EPF. The impact of the wind power penetration into the power grid on the market player's behaviour and his decisions has been studied by Usaola (2008), who estimated that the uncertainty of wind power supplied to the system leads to significant financial outcome reduction of the energy producers, reaching 10% of maximum obtainable revenue [2]. The same finding has been obtained by Crespo-Vasquez et al.(2017), who in the evaluation of the model constructed for decision-making of the windfarm owner underlined the loss of the incomes resulting from the uncertainty of wind power output - in this case the losses were constituting 4% of the total earnings [1]. The analysed publications indicate that the improvement of WPF becomes crucial from the perspective of enhancement of the effectiveness of market actions taken by its contributors [1,2,3]. It also should be pointed, that the uncertainty of the energy produced in a system has not only negative consequences. The presence of the day-ahead market, as well as the balancing market may be a field to multiply the member's revenues, who may speculate the prices and gain profits only from buying/selling the energy depending on the market or imbalance prices [2].

2.1. Wind Power Forecasting

The comprehensive and condensed study on WPF methods has been delivered by Zhao (2011), what gives a view on numerous aspects related to this issue. Above all, the two main approaches in WPF models can be distinguished: (i) physical: the models are created based on the measurements, technical data of the windmills and air parameters provided by the weather prognoses, (ii) statistical: including also the artificial intelligence, bases on the statistical models [5]. Among the most important issues related with the WPF is its scalability, what has been pointed by Rasheed et. al. (2014). The author emphasizes that for a two instances of exactly the same weather conditions in the windfarm the power output may differ significantly, what is caused by the complexity of the terrain on which the installation has been set up [6]. The fact that there are not universally optimal WPF models for all the windfarms has been highlighted by Banerjee et al. (2017), who demonstrated that the most appropriate modelling approach depends also on the evaluation criterion [7]. The achievable decrement of the WPF errors entails the necessity of knowing the primary sources of uncertainty. In the paper published by Monforti et. al.(2017) the authors have undertaken the attempt to detect and weight the main factors affecting inaccurate wind power predictions. The lack of comprehensive knowledge of the technical parameters of the wind farms and insufficient information on the wind fields are mentioned as the two main sources of WPF inaccurateness [8].

2.2. Market Prices Forecasting

The desire for knowing the market prices in advance with acceptable reliability has become naturally the subject of many studies. A remarkable focus has been put on forecasting the SPOT market prices [9,10,11]. Bessec et al. (2014) distinguishes three main modelling methods for predicting the energy prices on the market: equilibrium and game theory, simulation and time series forecasting methods [12]. The basic models for prediction of time series include smoothing methods like averaging, exponential smoothing (e.g. Brown's, Holt's Winter's methods). Although, the results of these models are burdened with relatively high prediction errors [9]. Throughout the numerous scientific works, the most attention is paid to the autoregressive (AR), Moving Average (MA) and their coupling - ARMA models, which successfully find and application in forecasting economy phenomena [13]. In the age of computers, the Artificial Neural Networks (ANN) as a branch of Computational Intelligence (CI) becomes increasingly popular in all range of predictions, mainly because of their forecasting accuracy and availability of dedicated software. Neural networks can be used successfully in circumstances which prevent the statistical methods to be applied. As one of the main advantages of the ANN one may mention its adaptability for complex, dynamic and nonlinear relations. On the other hand, Weron (2014) emphasises that the neural networks can be susceptible for unexpected, rapid changes in the process [14]. Kolmek and Navruz (2012) performed the parallel forecasting processes for the Turkish energy spot prices by means of the ARIMA and ANN model with the learning dataset constituting historical observations for time-range of 342 days. The latter model was burdened with smaller error, what was concluded as a main predominance of this method with respect to statistical techniques (15.60% MAPE for ARIMA vs 14.15% MAPE for ANN, calculated for a time horizon of 1 week) [15]. In his explicit study, Weron (2014) lists the strengths and weaknesses of the electricity spot prices forecasts in terms of the aforementioned methods, often being individual for a particular modelling approach. The compensation of the weaknesses may be achieved by combining the modelling tools by means of dedicated computer software. The hybrid EPF models become ascendingly applied in forecasting problems, often resulting in performance improvement [16], [17].

3. Methods

The calculations made in this project can be divided in two main segments – the first one will refer to evaluation of the wind power forecasts published for both examined countries in the ENTSO-E platform, while the second part will concern the usability of the ENTSO-E wind power forecast in the models predicting the SPOT market prices.

3.1. Wind generation forecast analysis

The analysis of wind power forecasts has been made by confronting the day-ahead wind generation forecasts and actual data, which have been published by ENTSO-E platform in hourly fragmentation. The data range has been assumed to 1 calendar year 2016, what resulted in 8760 observations. The error of the forecasts *e* will be calculated by subtracting the forecasts from actual measure. The statistical analysis of the obtained forecasting error will cover the calculation of the basic statistical measures presented in Table 1 [13].

Table 1 Statistical measures for wind power forecast evaluation

Statistical Measure	Mathematical Expression	
Average $\bar{e}$, MW	$\bar{e} = \frac{1}{N}\sum_{t=1}^{N} e$	(1)
Standard deviation σ, MW	$\sigma = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N}(e_t - \bar{e_t})^2}$	(2)
Kurtosis K	$K = \frac{\frac{1}{N}\sum_{t=1}^{N}(e_t - \bar{e})^4}{\sigma^4} - 3$	(3)
Skewness S	$S = \frac{N\sum_{t=1}^{N}(e_t - e)^3}{(N-1)(N-2)\sigma^3}$	(4)
MAPE, %	$MAPE = \frac{1}{N}\sum_{t=1}^{N} \lvert\frac{e_t}{P_t}\rvert \cdot 100\%$	(5)

Where: e – forecast error [MW], N – total number of observations, *t* – time instance, *P* – actual value

Moreover, the financial losses caused by inaccurate production planning and suffered by the wind energy suppliers in both countries will be estimated based on the ENTSO-E database. The calculations will be made using the actual and forecasted wind generation data, as well as their time-corresponding SPOT and balancing market prices for the calendar year 2016 in hourly fragmentation. The losses have been calculated assuming that the entire forecasted wind power is traded on the SPOT market, and the divergence between the wind forecast and actual production is traded on the balancing market, what can be expressed by the Equations 6 and 7.

$$L = \sum_{t=1}^{N} |E_t - E_t^*| * (I_t - M_t), \qquad for\ E_t - E_t^* < 0 \tag{6}$$

$$L = \sum_{t=1}^{N} |E_t - E_t^*| * (M_t - I_t), \qquad for\ E_t - E_t^* > 0 \tag{7}$$

Where: L – financial loss, E_t, E_t^* - actual and planned wind energy, M_t – spot market price, I_t – imbalance price.

3.2. SPOT market prices forecasting models

In order to comparatively examine the impact of the forecasted wind power on the SPOT market prices in both countries, the representative two modelling approaches have been selected from a wide range found in the literature: statistic (represented by ARMAX model) and heuristic (NARX model). For the evaluation of usability of the wind energy as an input variable to these models, their correspondents without the wind power information have been evaluated as well (ARMA and NAR models). The confrontation of the ARMA vs. ARMAX and NAR vs. NARX using the data from Poland and Portugal will allow to observe to what extent the models with additional external input perform better in two individual cases of Polish and Portuguese power markets.

3.2.1. Persistence model

Persistence models, also named as the naive models are characterized by their simplicity. The forecasted value of model takes the value of the last observation.

$$y_{t+1} = y_t \tag{8}$$

3.2.2. ARMA and ARMAX - Autoregressive Moving Average models

Box and Jenkins (1970) introduced a step-by-step methodology for modelling and estimation of time series by use of the autoregressive (AR) and Moving Average (MA) models [18]. On the other hand, the ARMAX model is the extension of the ARMA model by means of inclusion of the additional variable $u(t)$ in the model.

$$\begin{gathered} y(t) + a_1 y(t-1) + \cdots + a_{na}(t-n_a) \\ = b_1 u(t-1) + \cdots + b_{nb}(t-n_b) + \varepsilon(t) \\ +c_1 \varepsilon(t-1) + \cdots + c_{nc}\varepsilon(t-n_c) \end{gathered} \tag{9}$$

where: a_{na}- coefficients of the AR part of the model
c_{nc}- coefficients of the MA part of the model
b_{nb}- coefficients of the X part of the model
n_a, n_b, n_c – polynomial orders
$y(t)$ – past values of the modelled quantity (here SPOT prices)
$u(t)$ – past values of the external explaining variable (here wind power forecast)

If all the entities related to the external variable $u(t)$ were removed from the Equation 9, the model becomes ordinary ARMA model relying only on the past values of the explained variable. Successful adoption of the ARMAX model entails the necessity of fulfilling the particular requirements of the Box-Jenkins the method, as well as following the 3-step procedure: model identification, estimation of the parameters and model verification. To properly identify the model, the examined time series has to meet particular requirements. First of all, it has to be stationary (there is no trend observable and the variance is constant). Once the stationarity is not confirmed, the time series has to be modified to achieve stationarity. Secondly, the parameters of the model have to be determined by means of computational methods (e.g. maximum likelihood estimation or non-linear least-squares estimation). Further, the estimated parameters have to be verified statistically for proving their significance in the model. In this particular case, the ARMAX model data requirements have been assured by integration of the SPOT market prices time series:

$$\Delta y_t = y_t - y_{t-24} \tag{10}$$

The best model structure, i.e. polynomial orders will be obtained in iterative manner by means of looping capabilities of the software used.

3.2.3. NAR and NARX - Artificial Neural Network models

The origins of the ANN took place in 1943, when the first Artificial Neuron model has been introduced by McCulloch and Pitts. Contemporarily, ANN are commonly used in statistics and in signal processing. Despite the advanced development of this branch of science, the range of ANNs application is continuously expanding. The standard structure of the ANN consists of input units (vector of numbers provided by the user), hidden units (representing the intermediate calculations) and output units (vector of the model results) linked with particular weights. The weights reflect the importance of a given signal in the model – the higher is the weight value, the more significant is the input signal in the process of output determination. Therefore, the weights can take both negative or positive values [19].

The weights adjustment constitutes the learning process of the network, which in the case of this study has been made by use of Levenberg-Marquardt algorithm, considered as one of the most commonly used ANN learning techniques and characterised by high effectiveness in feedforward networks training [20]. The schematic representation of the NARX model has been shown in the Figure 1 on the example of the net consisting of 10 input variables and 5 hidden layers.

$$y(t) \ = \ f(y(t-1), y(t-2) \dots \ y(t-5), x(t-1), x(t-2) \dots \ x(t-5))$$

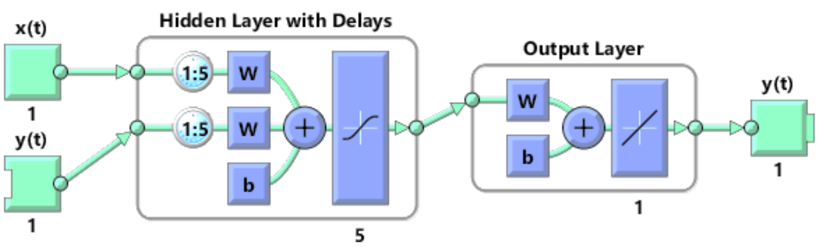

Figure 1 Graphical representation of NARX model – 10 input variables and 5 hidden layers (source: Mathworks)

If removing the x(t) signal from the NARX model, it becomes the NAR model with only the SPOT market prices past values as the explaining variables. The best model structure i.e. number of hidden layers and number of input signals (here – number of lags of time series) will be obtained in iterative manner by means of looping capabilities of the software used.

3.2.4. Forecasting approaches

The data used in the models was the wind generation forecast and SPOT market prices recorded in hourly fragmentation in the calendar year 2016.

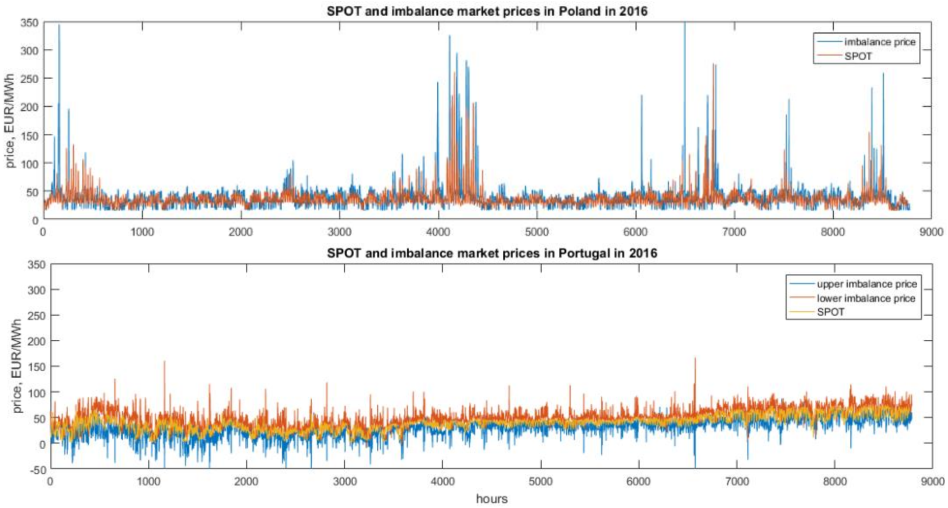

Figure 2 SPOT and imbalance market prices in Poland and Portugal in 2016

It has been decided to divide the data in two subsets: (i) learning dataset – consisting of observations from January to November 2016, which has been used for the estimation of the models and (ii) – testing dataset – December 2016, which has been used for verification of the models performance. Thus, the forecasts have been made in a step-ahead manner for the period of month December 2016. Since the ARMA model requires the stationarity of the subjected data, the SPOT prices time series have been integrated by subtraction of the price from hour *h-24* from price in hour *h* (Eq. 9). Additionally, it was decided to test several cases differed by the size of learning dataset, which have been defined as follows:

- Static Approach – fixed learning dataset – from January to November 2016 (case S1)
- Static Approach – fixed learning dataset – November 2016 (Case S2)
- Dynamic Approach – “moving” learning dataset – preceding week (case D1)
- Dynamic Approach – “moving” learning dataset – preceding 24 hours (case D2)

As the parameter allowing to evaluate the quality of obtained forecasts, the Mean Absolute Percentage Error (MAPE) has been selected and calculated for each of the abovementioned cases (Eq. 5), for Poland and Portugal, referred to the entire month of December 2016.

4. Results and discussion

The statistic description has been carried out to quantitatively compare the inaccuracies of wind power forecasts for both countries, including calculation of statistical measures, which have been presented in the Table 2.

Table 2 Statistical description of the wind Energy forecast error for Poland and Portugal in 2016

Statistical Measure	Poland	Portugal
Average, MW	118.23	7.52
Standard deviation, MW	173.00	353.30
Kurtosis	7.17	13.02
Skewness	0.399	-0.307
MAPE, %	15.00	24.20

Despite the fact that the Portuguese wind power forecast reveals much higher volatility in comparison with Poland (higher standard deviation, amplitude and MAPE values), the average value of the error is closer to the expected value of 0, being an order of magnitude lower than in the case of Poland. Moreover, a different tendency of error making can be observed, what is supported by opposite signs of the skewness.

The potential financial losses have been calculated assuming that the entire forecasted wind power is traded on the SPOT market, and the divergence between the wind forecast and actual production is traded on the balancing market. The results of the performed calculations have been presented in the Table 3:

Table 3 Financial losses resulting from wind generation forecast deviation in calendar year 2016

	Poland	Portugal
Total financial loss, €	1 900 592	20 812 563
Number of hours in 2016, when forecast deviation brought benefits	4510	814
Total volume of imbalanced energy, MWh	1 358 182	1 944 235
Unit cost of imbalanced energy, €/MWh	1.40	10.70

The obtained results show that despite the similar order of magnitude of cumulative imbalanced power in both countries, the improper forecasting brings around 10 times higher losses in Portugal. This has an origin in balancing market regulation – in Portugal, there are two levels of balancing market price, depending on the character of imbalance (surplus/deficiency). On the other hand, in Poland there is only one universally valid imbalance price, what gives an opportunity for market speculation. Nevertheless, it should be emphasized that the average level of electricity price in both countries differs, what could to some extent amplify the difference in obtained results.

The forecasting results with use of ARMA, ARMAX, NAR and NARX models have been presented in the Table 4. The results, for which a given case of particular model with wind power information performed better than its counterpart without inclusion of this quantity have been highlighted blue. The information of the key model parameters has been shown as well.

For having a perspective on the financial burden correspondent to the inaccuracy of the performed forecasting models, the total uncertainty of sales of the wind energy (SU) in December 2016 (744 hours) has been calculated according to the equation 11, under assumption that the entire wind energy is traded on the SPOT market:

$$SU = MAPE \cdot \sum_{t=1}^{744} E_t^* \cdot M_t \tag{11}$$

Where SU – total sales uncertainty [EUR], E_t^*– traded forecasted wind energy volume in an hour t [MWh], M_t – SPOT market price in an hour t [EUR/MWh].

Table 4 Comparison of ARMA and ARMAX SPOT prices forecasting models

POLAND										
CASE	ARMA				ARMAX					**SU_{ARMA}-SU_{ARMAX}**
	PARAMETERS		MAPE	SU_{ARMA}	PARAMETERS			MAPE	SU_{ARMAX}	
	p	q		[EUR]	na	nb	nc		[EUR]	[EUR]
S1	1	0	6.98%	3 448 565	1	0	0	6.97%	3 443 624	-
S2	1	0	6.90%	3 409 040	1	0	0	6.89%	3 404 099	-
D1	1	2	7.04%	3 478 209	2	2	0	6.79%	3 354 693	123 516
D2	1	0	8.23%	4 066 145	1	0	1	6.81%	3 364 574	-

PORTUGAL										
CASE	ARMA				ARMAX					**SU_{ARMA}-SU_{ARMAX}**
	PARAMETERS		MAPE	SU_{ARMA}	PARAMETERS			MAPE	SU_{ARMAX}	
	p	p		[EUR]	na	nb	nc		[EUR]	[EUR]
S1	5	4	3.66%	2 262 710	5	4	5	3.57%	2 207 070	55 640
S2	4	4	3.71%	2 293 622	5	2	5	3.57%	2 207 070	86 552
D1	3	3	4.24%	2 621 282	4	2	4	3.64%	2 250 346	370 936
D2	3	3	6.09%	3 765 002	3	5	3	7.77%	4 803 623	-

The S1, S2 and D2 cases have not been highlighted, because in these examples the ARMAX model's nb coefficient was zero, which is the order of polynomial composed of external variable values, what means that actually the ARMAX model becomes ordinary ARMA model.

Table 5 Comparison of NAR and NARX SPOT prices forecasting models

POLAND										
CASE	NAR				NARX					**SU_{NAR}-SU_{NARX}**
	PARAMETERS		MAPE	SU_{NAR}	PARAMETERS			MAPE	SU_{NARX}	
	delays	hidden layers		[EUR]	delays	ex. Input delays	hidden layers		[EUR]	[EUR]
S1	1	5	6.71%	3 315 168	3	5	2	6.74%	3 329 990	-
S2	2	2	6.55%	3 236 118	5	5	2	6.63%	3 275 643	-
D1	2	3	7.54%	3 725 241	2	1	1	8.12%	4 011 798	-
D2	3	4	9.83%	4 856 647	4	4	4	8.78%	4 337 880	518 767
PORTUGAL										
CASE	NAR				NARX					**SU_{NAR}-SU_{NARX}**
	PARAMETERS		MAPE	SU_{NAR}	PARAMETERS			MAPE	SU_{NARX}	
	delays	hidden layers		[EUR]	delays	ex. Input delays	hidden layers		[EUR]	[EUR]
S1	5	1	3.74%	2 312 169	5	2	5	3.63%	2 244 164	68 005
S2	4	5	3.71%	2 293 622	4	5	3	3.64%	2 250 346	43 276
D1	1	1	3.88%	2 398 720	5	5	5	3.67%	2 268 893	129 828
D2	3	4	4.58%	2 831 479	5	4	1	4.20%	2 596 553	234 926

The analysis of the above tables allows to conclude that comparing the forecasting results globally, the Portuguese SPOT market prices are significantly more predictable than in the case of Polish market using the models constructed for the purpose of this study. Another finding is that usually the dynamic cases perform worse than the static ones – it is better for model estimation to include wider ranges of data.

As regards the influence of the wind power forecast on the models for predicting the SPOT price, a certain improvement can be observed in almost all the cases of the models for Portuguese data. Additionally, in the right-adjacent column the difference between the Sales Uncertainty of the models without and with inclusion of the wind generation forecast has been calculated – as it can be observed, the sales uncertainty decrease varied between 55 000 EUR to around 235 000 EUR in the case of models based on Portuguese data. Contrarily, in the case of Poland, the addition of expected wind power production brought no added-value to the models in terms of accuracy. The results answer the fundamental question of this study, because as it is observed, the impact of wind power on the market prices is not unequivocal. An application of a given model with wind power variable as input occurred to be valuable in the case of Portugal, while in Poland not.

Conclusions

The analysis of the wind power forecasts for Poland and Portugal resulted in obtaining significant forecasting errors, based on calculations made by use of data from ENTSO-E platform. The remarkable discrepancies have been observed for both analysed countries. Analysis of the wind forecasts error distribution revealed that there exists a different preference in estimation of the wind generation forecast among the countries, i.e. in Portugal, the forecast more often predicted lower values than the actual ones. In the case of Poland, this preference was opposite. This finding opens a new research opportunity which would concern the application of systematic error correction in the overall wind production forecasts. Calculation of the financial losses from inaccurate wind power forecasts led to the conclusion that the uncertainty of the wind energy production planning/forecasting results in remarkable potential income losses for the wind energy producers, reaching millions of EUR in global(national) scale. As it occurred, in the Polish case there exists a large possibility of market speculation, since in many instances the sales on the balancing market were more profitable than in the SPOT market. Analysis of the SPOT price forecasting models shows that in the case of Poland, the usability of wind power as the input to a particular considered model is doubtful. On the other hand, a decrement of MAPE values has been noticed when adding the wind power input variable to the models basing on Portuguese data, what translated into lower sales uncertainty of generated wind power. These opposite observations reveal that the advantage of models including wind power information is not equivocal among the individual countries. The comparative analysis carried out within this work revealed a potential of commercial application – for example, in Poland, one can find offers providing IT solutions for performing predictions in the Iberian market. The analysis focused on detection of main differences among two individual market systems may be desirable from the perspective of comparison of commercial IT forecasting tools.

Literature

[1]. González-Aparicio J., Zucker A., *Impact of wind power uncertainty forecasting on the market integration of wind energy in Spain*, Applied Energy 159 (2015) 334–349,

[2]. Usaola J. *Participation of wind power in electricity markets*, preliminary report from 6th FP European Project (Reference 38692) and IEMEL - research Project of the Spanish Ministry of Education (Reference ENE2006-05192/ALT), Universidad Carlos III de Madrid, 2008

[3]. Jonsson T. et al., *Forecasting electricity SPOT prices accounting for wind power predictions*, IEEE transactions on sustainable energy, vol. 4 (2013) 210 - 218

[4]. Erni D., *Day-ahead electricity Spot prices – fundamental modelling and the role of expected wind electricity infeed at the European Energy Exchange,* PhD dissertation, University of St. Gallen, 2012

[5]. Zhao X., Wang S., Li T., *Review of Evaluation Criteria and Main Methods of Wind Power Forecasting,* Energy Procedia 12 (2011) 761 – 769,

[6]. Rasheed A., S¨uld J. K., Kvamstdal T., *A Multiscale Wind and Power Forecast System for Wind Farms*, Energy Procedia 53 (2014) 290 – 299,

[7]. Banerjee A., Tian J., Wang S., Gao W., *Weighted Evaluation of Wind Power Forecasting Models Using Evolutionary Optimization Algorithms*, Procedia Computer Science 114 (2017) 357–365,

[8]. Monforti F., Gonzalez-Aparicio I., *Comparing the impact of uncertainties on technical and meteorological parameters in wind power time series modelling in the European Union*, Applied Energy 206 (2017) 439–450,

[9]. Misiorek A., Weron R., *Forecasting SPOT electricity prices with time series models*, The European Eleectricity Market EEM-05 – conference proceedings, Poland 2005

[10]. Voronin S., Partanen J., *Price forecasting in the day-ahead energy market by an iterative method with separate normal price and price spike frameworks,* Energies Vol. 6 Issue 11 (2013), 5897-5920

[11]. Franco J., Blanch E. et al., *Forecasting day ahead electricity price using ARMA methods*, research report from project carried in terms of "outgoing" program (ETSEIB), Universidade de Sao Paolo, Brasil 2015

[12]. Bessec M., *Forecasting electricity spot prices using time-series models with a double temporal segmentation*, 2nd International Symposium on Energy and Finance Issues (ISEFI-2014), Mar 2014, Paris, France. p.34

[13]. Witkowska D., *Podstawy ekonometrii i teorii prognozowania,* Oficyna Ekonomiczna, 2006, ISBN 83-7484-029-3

[14]. Weron R., *Electricity price forecasting: a review of the state-of-the-art with a look into future,* International Journal of Forecasting Vol. 30 (2014) 1030–1081

[15]. Kolmek M.A., Navruz I., *Forecasting of the day-ahead price in electricity balancing and settlement market of Turkey by using artificial neural networks*, Turkish journal of Electrical Engineering & Computer Science Vol. 23 (2015) 841-852

[16]. Tan Z., Zhang J., et. al., *Day-ahead electricity price forecasting using wavelet transform combined with ARIMA and GARCH models*, Applied Energy Vol. 87, Issue 11 (2010), 3606-3610

[17]. Shafie-khah M., ParsaMoghaddam M., *Price forecasting of day-ahead electricity markets using a hybrid forecast method*, Energy Conversion and Management Vol. 52, Issue 5, (2011) 2165-2169

[18]. Box G.M.P., Jenkins G.M. et al. *Time series analysis: forecasting and control*, Prentice Hall, 1994, ISBN: 978-1-118-67502-1

[19]. Fausette L., *Fundamentals of Neural Networks – Architecture, algorithms and applications,* Florida Institute of Technology 1994, ISBN 978-0133341867

[20]. Madsen K., Nielsen H.B., Tingleff O. *Methods for non-linear least squares problems, 2nd Edition*, April 2004, Technical University of Denmark