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Aleksandra AUGUSTYN[1], Jacek KAMIŃSKI[1]

A review of methods applied for wind power generation forecasting

ABSTRACT: The dynamic development of wind power in recent years has generated the demand for production forecasting tools in wind farms. The data obtained from mathematical models is useful both for wind farm owners and distribution and transmission system operators. The predictions of production allow the wind farm operator to control the operation of the turbine in real time or plan future repairs and maintenance work in the long run. In turn, the results of the forecasting model allow the transmission system operator to plan the operation of the power system and to decide whether to reduce the load of conventional power plants or to start the reserve units.

The presented article is a review of the currently applied methods of wind power generation forecasting. Due to the nature of the input data, physical and statistical methods are distinguished. The physical approach is based on the use of data related to atmospheric conditions, terrain, and wind farm characteristics. It is usually based on numerical weather prediction models (NWP). In turn, the statistical approach uses historical data sets to determine the dependence of output variables on input parameters. However, the most favorable, from the point of view of the quality of the results, are models that use hybrid approaches. Determining the best model turns out to be a complicated task, because its usefulness depends on many factors. The applied model may be highly accurate under given conditions, but it may be completely unsuitable for another wind farm.

KEYWORDS: wind power, forecasting, physical methods, statistical methods, hybrid methods, wind power integration

[1] Mineral and Energy Economy Research Institute of the Polish Academy of Sciences, Kraków, Poland; e-mail: augustyn@min-pan.krakow.pl; kaminski@min-pan.krakow.pl

Introduction

Finite resources of fossil fuels and the emerging climatic changes have contributed to the search for new solutions in the field of energy production. In order to promote renewable energy sources (CRES) around the world, support mechanisms, aimed at making investments in this area economically attractive, are used. The dynamic development of these investments is confirmed by the data presented in the international report on renewable energy sources. In 2016, the total installed capacity of RES amounted to 2.179 GW, what is an increase of more than two thousand percent compared to 2007, when the installed capacity was 924.2 GW (IRENA 2018). Wind power is the most dynamically developing sector of renewable energy. Only in 2017, 53 GW of new capacities, worth USD 278.5 billion, were commissioned. The total wind power capacity installed worldwide reached 540 GW (Global Wind Energy Council 2017) at the end of 2017.

The dynamic development of wind power is a result of a positive impact both on climate change mitigation and the reduction of environmental pollution (de Jong et al. 2016), and technological development, and the decreasing costs of energy production (Schleich et al. 2017). However, it should be borne in mind that the increasing number of wind farms connected to the power system creates numerous threats to its proper functioning. Countries with large wind power capacities suffer major consequences in the field of power system operation and the quality control of the electricity supplied (Perez-Arriaga and Batlle 2012). Most of the existing power systems were designed for large coal-fired units, whose operation can be controlled. The electricity production in wind power plants, in turn, is primarily determined by weather conditions, which are not dependent on the actual power demand. According to Betz's law, wind power in an open air stream is proportional to the third power of the wind speed. As a consequence, the level of electricity production in a wind farms depends primarily on such factors as wind speed and winding time (Herrero-Novoa et al. 2017).

It is commonly known that wind, whose power is converted in wind turbines, is caused by differences in the atmospheric pressure caused, in turn, by temperature changes in a given area. Air masses move from high pressure areas to low pressure areas due to pressure differences. The stronger the pressure gradient, the stronger the wind. The variability of weather conditions is the reason why wind power is unstable, which leads to a number of problems associated with the integration of wind farms with power systems and requires new solutions in order to balance the supply and demand in the electricity market (Marčiukaitis et al. 2017).

The possible solution is a reliable forecasting of wind power generation. The random operation of wind power plants is the reason why reliable forecasting of wind power production is a very complex task. However, its development is crucial for energy trading and the safe operation of the national power system (Okumus and Dinler 2016). An accurate forecast is of particular importance for the power system operator, who is responsible for balancing the system and addressing the system limitations. It enables, among others, controlling the operation of generating units responsible for reserve capacities (Lei et al. 2009).

Therefore, wind power generation forecasting is the center of interest of many researchers, constantly improving the existing approaches and developing new, more reliable forecast models. In light of the above, this paper is aimed at reviewing wind power generation forecasting methods. It is a starting point for the further analysis and development of new forecasting methods.

1. The classification of wind power generation forecasting methods

The main role of wind power generation forecasting models is to provide information on the amount of production which can be expected in the next few minutes, hours, or days. The time horizon of the forecasting method is one of the main factors influencing the choice of a specific approach. In accordance with the above classification, the methods are divided into four different categories. The following types of forecasting methods can be distinguished (Chang 2014):

- Very short term forecasting (ultra-short-term forecasting): from few minutes up to one hour,
- Short-term forecasting: from one hour to several hours ahead,
- Medium-term forecasting: from several hours up to one week,
- Long-term forecasting: from one week up to a year or more.

It should be noted that there are other classifications available. Forecasting methods with different time horizons are discussed in numerous works. It is also worth noting that in some publications, medium-term forecasts are omitted (Zhang et al. 2014).

The choice of the time horizon of the forecast is determined by the need to use its results. According to the mentioned classification, very-short-term forecasts are used, among others, when making decisions regarding current activities in the electricity market and the control of wind turbines in real time (Gangui et al. 2012). What is more, the results of very-short-term forecasts are used for regulatory activities. On the other hand, short-term forecasts are useful for transmission system operators when making decisions on balancing the power system. In addition, they are used to schedule the operation of the wind farm. Medium-term forecasts are used to plan the operation of the power system, including wind farms, and to make decisions related to energy trading in the long run. Based on the obtained results, the operator may increase or reduce the conventional unit load and make decisions regarding operating reserves. Information obtained from long-term forecasts allow planning of repairs and maintenance of wind turbines and the analysis of the development of electricity generation systems. However, it should be borne in mind that simple models are not useful in the case of long-term forecasts. In turn, even complex models are subject to a greater error than in the case of short-term forecasts.

The choice of a forecasting method also depends on the number of wind turbines. The following methods ca be distinguished: spot (point) forecast (the production is forecasted for one wind turbine), forecasting for a given wind farm, and for the whole region. The test results indicate that the forecast error largely depends on the number of turbines (or farms) and their distribution. Its value decreases with the increasing number of turbines in the area covered by the forecast. In Germany, the errors of forecasts for wind farms ranged from 10 to 15%, while in the case of forecasts for the whole area, they were in the range of 5–6% (Ernst et al. 2007).

Another criterion for classifying forecast models is the approach in the calculation process. The most advanced wind power forecasting methods include two basic approaches: physical (deterministic) and statistical. Physical models are primarily based on physical relationships between the weather phenomena, location of a wind farm, terrain conditions, and the energy production. In this approach, Numerical Weather Prediction (NWP) data, based on atmospheric dynamics, are also used as input data. In turn, the statistical approach is primarily based on the analysis of large historical data sets and forecasts based on past relationships.

In addition, other distinctions, based on the input data (models using or not using the results of NWP models) and the obtained forecast results (the production is forecasted based on the predicted wind speed or directly, without a previous step in which the wind speed is forecasted) (Zhao et al. 2011).

2. Wind power forecasting methods

2.1. Persistence method

This is the simplest method of wind power forecasting. It is based on the simple assumption that the wind power P at time $t + \Delta t$ will be the same as it is when the forecast is made t (Lange and Focken 2005). This relationship is described by using the following formula (1).

$$P(t + \Delta t) = P(t) \tag{1}$$

The above relationship is useful primarily for ultra-short-term forecasts for wind farms with turbines spread over a large area. The reason for this is the persistence of wind in the short time horizon and the fact that individual turbines do not react simultaneously to changes in the wind speed (Karkoszka 2010). The accuracy of persistence models decreases with the lengthening of the forecast horizon.

2.2. Physical methods

The physical approach uses the wind farm data and numerical weather predictions; the use of the downscaling method allows the wind conditions that prevail at the hub height to be determined. The more accurate the parameters describing the wind farm and its surroundings, the more accurate are the results of wind speed at the selected height. The improved results are sequentially combined with the corresponding power curve to calculate the amount of energy produced. The diagram describing the steps in the physical approach is presented in Figure 1. The discussed approach does not require the use of historical data on wind speed and energy produced. However, obtaining accurate data on physical phenomena and the topography of the terrain is complicated.

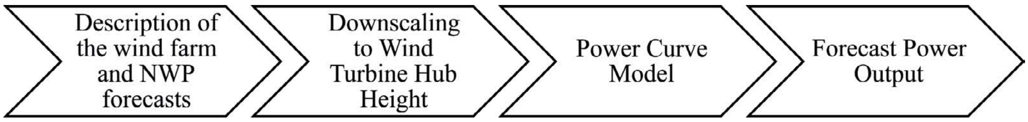

Fig. 1. A diagram describing the physical approach (Jung and Broadwater 2014)

Rys. 1. Schemat opisujący podejście fizyczne

2.3. Numerical weather prediction models

The behavior of the Earth's atmosphere is described by non-linear partial differential equations. Due to the changing nature, it is impossible to solve them in an analytical way. However, it is possible, however, to obtain approximate solutions of these equations using numerical methods. In the case of numerical models, meteorological fields are described using a finite number of points. The calculations are, in turn, performed at points referred to as grid nodes. By determining the horizontal distances between grid nodes, it is possible to specify the resolution of the model. The higher the resolution, the more accurate the forecast. Depending on the spatial horizon, numerical models can be divided into global, regional, and mesoscale models (Pietrek 2006). To perform numerical calculations, physical equations describing the phenomena occurring in the atmosphere, such as temperature and pressure over time, changes in air humidity, and flow velocity, are used. In view of the above, NWP models are focused not only on forecasting wind speeds, but also on atmospheric conditions at a specific time horizon. Global forecasting models are primarily focused on land phenomena.

The choice of the NWP model has a fundamental impact on the development of the wind power forecasting method. In practice, it is necessary to consider the following criteria: forecast time horizon, geographical area, spatial and temporal resolution, required accuracy, and acceptable calculation time. It is possible to use more than one NWP model. It has been shown that the use of more than one NWP model enables more accurate wind power forecasting (Nielsen et al. 2007).

To decide whether to use data from the NWP model as an input variable of the forecast, it is necessary to determine the time horizon of the forecast. Numerical weather prediction models have a significant advantage over time series models for forecasts with a time horizon from three to six hours (Giebel et al. 2011).

2.4. Statistical methods

Time series models and artificial neural network models are the most popular statistical models. Time series models use a statistical approach to forecast the average hourly wind speed or directly forecast wind power production. These models provide accurate forecasts of the average monthly or annual production.

The time series models used in wind power studies include, among others:
- Autoregressive model (AR),
- Moving-average model (MA),
- Autoregressive–moving-average model (ARMA)
- Autoregressive integrated moving average (ARIMA) model.

The conventional statistical methods are based on classical linear statistical models. The accuracy of these forecasting approaches depends primarily on the parameters used. The discussed methods are mostly used for very-short and short-term forecasting. The developed models are usually not complicated, require low computing power and can quickly provide the required information.

In recent years, methods based on machine learning or artificial intelligence are being used more frequently. Another approach is modeling using an artificial neural network (ANN). Artificial neural networks are trained by historical data sets to understand the relationship between output and input variables. The ANN model consists of the input layer, one or more hidden layers, and the output layer. Each layer contains numerous neurons that connect with each other through connections between successive layers of multi-layered networks; the neurons are connected between layers on a peer-to-peer basis (usually, neurons of nearby layers are connected). This allows for modeling the nonlinear dependence of the output variable on the input variable. One of the advantages of the ANN approach is the model's ability to self-learn, self-organize, and self-improve. In addition, such a model is relatively simple to build, because it does not require explicit mathematical expressions. Furthermore, the calculation time is relatively short. The first step when building the ANN model is the selection of the topology of a neural network. These include, among others, one-way networks, where the information moves in only one direction, or recurrent neural networks, i.e. networks whose neurons send feedback signals to each other or competitive learning networks (Stefanowski 2006). The next step is the selection of the appropriate learning algorithm. Learning can be supervised – the task of the network is to learn the function determining the dependence of the output variable on the input variables based on the historical data set consisting of the input-output pairs. The second option is unattended learning, determining ANN parameters depending on the data set and the cost function. The third type is reinforcement learning, in which input data are generated through interaction with the environment (Jung and Broadwater 2014).

Another approach is the combination of artificial neural network and fuzzy logic methods, also referred to as ANN-Fuzzy. The fuzzy logic is an extension of classical logic; fuzzy-set variables range from zero to one. The combination of fuzzy logic with ANN can be used when other methods do not give satisfactory results or are too time-consuming. In addition, it allows the element of human reasoning to be introduced. The use of the ANN-fuzzy has already been discussed in (Sharifian et al. 2018).

In addition, other statistical wind power forecasting models described in the literature include:

- The k-nearest neighbors algorithm (Mangalova and Shesterneva 2016),
- Evolutionary optimization algorithms (Banerjee et al. 2017),
- Wavelet transform for short-term wind power forecasting (Catalão et al. 2011),
- Support vector machine (Kong et al. 2015).

2.5. Hybrid methods

Generally, physical models are based on meteorological conditions, while statistical models are based on a large amount of historical data on energy production (without taking meteorological conditions into account). Currently, most forecasting models use both approaches at the same time (hybrid method). The main objective of the hybrid approach is to improve the efficiency and quality of forecasts by using the strengths of each approach. Therefore, the hybrid model uses physical relationships to capture the air flow in the region surrounding the turbines and advanced statistical modeling to make use of the relationships between all parameters of the physical approach. The integration of these approaches reduces the risk of erroneous forecasts during extreme events, such as storms. However, it should be borne in mind that combining prognostic methods is not always better than using a single approach (Hibon and Evgeniou 2005).

3. The accuracy of forecasting methods

Due to the large number of possible approaches and their integration (hybrid models) it is not possible to clearly indicate which method will allow the most accurate forecast to be obtained. It should be borne in mind that selecting the best model for wind power forecasting is a very complex task. A given model may be useful under certain atmospheric conditions, while it may produce erroneous forecasts under others.

In order to obtain information on the usefulness of the forecast for given parameters, the forecast error should be calculated. The literature of the subject provides many measures for assessing the quality of the forecasts. They include, among others:

- The mean error (ME):

$$ME = \frac{1}{n}\sum_{t=1}^{n}\left(y_t - y_t^P\right) \tag{2}$$

where:

- n – number of observations, $t = 1, 2, 3, \ldots, n$,
- y_t – measured value,
- y_t^P – the forecasted value.

- The mean absolute error (*MAE*):

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|y_t - y_t^P\right| \tag{3}$$

- The mean absolute percentage error (*MAPE*):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|y_t - y_t^P\right|}{y_t}\cdot 100\% \tag{4}$$

- The mean square error (*MSE*):

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\left(y_t - y_t^P\right)^2 \tag{5}$$

- The root mean square error (*RMSE*):

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(y_t - y_t^P\right)^2} \tag{6}$$

- The standard deviation of errors (*SDE*):

$$SDE = Std\left(y_t - y_t^P\right) = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\left(y_t - y_t^P\right) - Avg\left(y_t - y_t^P\right)\right)^2} \tag{7}$$

where:

Std – standard deviation,
Avg – mean value.

The forecast error is influenced by many factors. They include, among others:

- The forecast time – the shorter it is, the smaller the forecast error. The mean absolute error for short-term forecasts is in the range of 5–15%, while for forecasts for one to two days in advance it increases to 21%, and in the case of long-term forecasts it reaches up to 25% (Liang et al. 2016);
- Surface roughness – the forecast error is generally higher for wind farms located on varied terrain than for those located on flat surfaces (Giebel et al. 2011);
- Season – The forecast error in the winter season is smaller than in the case of the summer season, which is mainly related to a higher wind speed and storms in the summer season (Lange and Focken 2005);
- Atmospheric conditions prevailing at a given location – the more stable they are, the smaller the forecast error;
- Atmospheric pressure – the higher atmospheric pressure, the smaller the forecast error.

Conclusions

The forecasting process, especially when taking the influence of atmospheric conditions that are characterized by a high variability into account, is a very complex process. A characteristic feature of the correctly developed model is the mapping of the system and the links between its elements, to obtain the best possible quality of forecasts. It should therefore be noted that some relationships are not considered. If the introduction of a given element or relationship does not improve the functioning of the model, it should be omitted. The development of an appropriate, highly accurate forecasting method requires not only the knowledge of mathematical expressions, physical phenomena, and economic dependencies, but also the experience and intuition of the modeler.

The presented paper is aimed at systemizing the current state of knowledge in the area of approaches used in wind power forecasting. When it comes to the discussed methodologies, the greatest emphasis is placed on the hybrid approach, allowing taking advantage of both the physical and statistical approaches. However, it should be noted that these models are not effective in the case of small computational resources.

The method based on the combination of artificial neural networks and fuzzy logic is more commonly used in recent years. This method does not require complex equations describing atmospheric phenomena. However, it uses historical data sets and neural connections to independently determine the relationship between the input variable and the output parameters. The larger the set of historical data, the more effective the learning process and the more accurate forecasts, even including weather anomalies. Introducing the element of fuzzy logic makes the model more flexible. The analysis of the current state of wind power forecasting has confirmed that a significant increase in the development of forecasting methods is expected.

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Aleksandra Augustyn, Jacek Kamiński

Przegląd metod prognozowania produkcji w elektrowniach wiatrowych

Streszczenie

Dynamiczny rozwój energetyki wiatrowej w ostatnich latach generuje zapotrzebowanie na narzędzia do prognozowania produkcji w elektrowniach wiatrowych. Informacje pozyskane z wykorzystaniem modeli matematycznych są użyteczne zarówno dla właścicieli farm wiatrowych, jak i dla operatorów systemów dystrybucyjnych i przesyłowych. Posiadając informacje dotyczące przewidywanej produkcji, operator elektrowni wiatrowej może sterować pracą turbiny w czasie rzeczywistym lub zaplanować remonty i prace konserwacyjne w przyszłości. Z kolei operator systemu przesyłowego, dysponując wynikami modelu prognostycznego, może zaplanować pracę systemu elektroenergetycznego, decydując się na redukcję obciążenia w elektrowniach konwencjonalnych lub na włączenie jednostek rezerwowych.

Niniejszy artykuł przedstawia przegląd obecnie stosowanych metod prognozowania produkcji w elektrowniach wiatrowych. Ze względu na charakter danych wejściowych wyróżnia się metody fizyczne oraz statystyczne. Podejście fizyczne opiera się na wykorzystaniu danych związanych z warunkami atmosferycznymi, ukształtowaniem terenu i charakterystyką farmy wiatrowej. Najczęściej bazuje na modelach numerycznych prognoz pogody NWP (ang. *numerical weather prediction*). Z kolei w podejściu statystycznym wykorzystuje się zbiory danych historycznych w celu ustalenia zależności zmiennych wyjściowych od parametrów wejściowych. Jednak za najkorzystniejsze pod względem jakości uzyskiwanych wyników uznaje się modele, które wykorzystują podejścia hybrydowe. Określenie najlepszego modelu okazuje się zadaniem skomplikowanym, ponieważ jego użyteczność zależy od wielu czynników. Model zastosowany w danych warunkach może charakteryzować się wysoką dokładnością, natomiast być kompletnie nieprzydatny dla innej farmy wiatrowej.

Słowa kluczowe: energetyka wiatrowa, prognozowanie, metody fizyczne, metody statystyczne, metody hybrydowe, integracja energetyki wiatrowej