

Optimizing the mathematical model for prediction of energy production in wind power plants

Abstract. Wind Power Plants are classified as a power energy sources with non-stable supply of electric energy. It is necessary to back up power energy from Wind Power Plants for stable electric network operation. We can set an optimal value of back up power energy with using variety of prediction models. Mathematical model for prediction of Wind Power Plant energy was developed at the Technical University of Ostrava within research project MSM 6198910007. There are introduced partial results of predictive model verification.

Streszczenie. Elektrownie wiatrowe zalicza się do źródeł energii charakteryzujących się niestabilnością dostaw energii elektrycznej. Dla stabilnej pracy sieci niezbędne jest rezerwowanie energii z elektrowni wiatrowych. Optymalny stopień rezerwowania można wyznaczyć przy użyciu różnych modeli prognostycznych. Na Uniwersytecie Technicznym w Ostrawie został opracowany w ramach projektu MSM 6198910007 matematyczny model predykcji energii z elektrowni wiatrowych. Przedstawiono częściowe wyniki weryfikacji modelu predykcji. (*Optymalizacja modelu matematycznego do prognozowania produkcji energii z elektrowni wiatrowych*)

Keywords: prediction, mathematical model, wind power plant

Słowa kluczowe: predykcja, model matematyczny, elektrownia wiatrowa

Introduction

During operation of electricity supply system to which a number of renewable sources with unstable power supply are connected, significant fluctuations are happening in the magnitude of the power delivered from these renewable sources and thus the large volume of regulation energy is needed to maintain the system operation in a stable, safe and economically optimum state. At the same time there is a direct proportion between the size of installed capacity in renewable electricity sources and the size of the reserves for regulation energy coverage to compensate the lack of power from these sources.

In the Czech Republic the magnitude of installed capacity in wind and photovoltaic power plants grew enormously and the total installed capacity in individual types of power plants is shown at Fig. 1.

Diagram at Fig. 1 shows the installed power as of 28 Feb 2010. However, the Czech Regulation Authority registers the applications for power plants connection to electricity supply system 3500MW as of 31 Dec 2009. In the event all the applications will be implemented, there will be a problem to purchase enough regulation power as due to the obligation to buy all power most probably steam power plants will have to be put out of operation that participate in system regulation. Subsequently there will not be enough power in rotary sources to provide regulation services to cover the needs of the electricity power supply operator. Another question is the impact of regulation reserve size on total economy of the operation. As it was stated earlier together with growing installed power in wind and photovoltaic power plants the size of necessary reserves is growing. Thus it is necessary, taking into account the price of regulation power, to determine the size of the regulation reserve as accurately as possible. The regulation power size is set, among others, according to the assumed volume of electricity production from all sources connected to the supply system. That is why the prediction of electricity production from unstable wind and photovoltaic sources is necessary to determine precisely the reserves size and thus minimizing the costs associated with securing necessary regulation power. Further in this paper there is a detailed description of only the status of wind power plants as at the VSB-TU Ostrava a prediction system has been developed in recent years for predicting electric power in just wind power plants. Currently the prediction system for electric

power production in photovoltaic power plants is being developed.

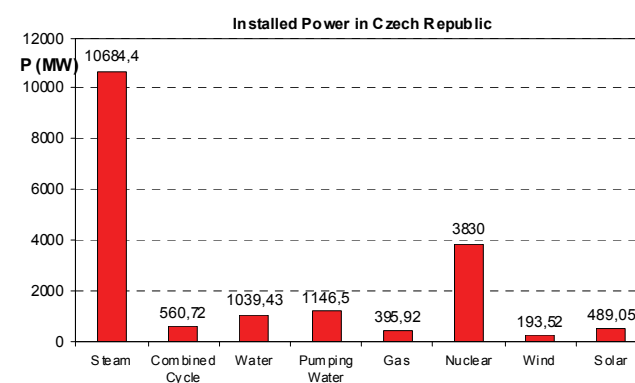


Fig.1. Installed Power in Czech Republic

At the moment a couple of prediction systems exist and are used worldwide which can predict with a certain accuracy the electric power production from wind power plants. These are for instance systems ANEMOS Project [2], WIND POWER PREDICTION TOOL [17], PREDICTOR [10], SCIRROCO [14], METEOLÓGICA [7], eWIND [3] or SOWIE [15]. The issue with these prediction systems is the localization in the area where the prediction is carried out. None of systems is localized for the territory of the Czech Republic. Only several institutions deal in the long-run in the Czech Republic with electric power prediction among which there are the Air Physics Institute of the Academy of Science of the Czech Republic, the Electricity Industry of the VSB-TU Ostrava and since recently also the University in Plzeň.

Description of the VSB-TUO prediction model

The prediction model developed at the VSB-TU Ostrava is based on using the data on wind velocity and direction for individual wind plants and the correction of this data by means of a correction system and subsequent recalculation of the power curve to assumed power of a wind plant. Meteorological data for the prediction model is used from the WRF meteorological prediction model. However, the prediction model is designed generally and that is why it is possible relatively quickly and easily to implement data from any other model whose forecasts cover a monitored

area. These are models such as HIRLAM, ECMWF, GFS, WRF, UMPL or Aladin. The accuracy of meteorological data prediction depends on the size of the prediction square for which wind velocity and direction are considered constant. Such a simplification is applied to prediction systems and its aim is to simplify prediction calculation.

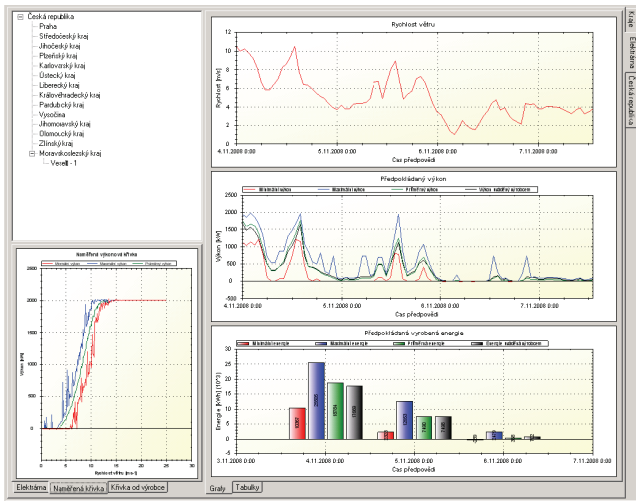


Fig.2. VSB-TU Ostrava prediction system

From the meteorological prediction model we can get the information on wind velocity and direction. This information needs to be revised for a specific wind power plant so that the required accuracy of electricity power production prediction from wind plants is secured. In most case four corrections are made:

- The correction of wind velocity and direction for a given WPS as a result of placing the monitored WPS in a given prediction square.
- The velocity correction considering the height of the WPS hub.
- The wind velocity correction considering wind direction.
- The wind velocity correction considering current temperature and pressure.

The above corrections are implemented in most of the prediction systems. The impact of individual corrections on prediction accuracy varies for each correction. The velocity and direction correction has the largest influence due to placing the wind power station in a prediction square and the correction of wind velocity with respect to wind direction. At the same time these corrections are the most difficult to execute. Remaining corrections have only minimum impact on resulting prediction accuracy in the size of approximately one percent. At Fig. 2 one of the basic screens of the VSB-TU Ostrava prediction system can be seen. In the left-bottom part there are individual regions and wind power plants, at the bottom a power curve can be seen in three scenarios for a specific monitored wind plant. It is a measured power curve where the three displayed options correspond to the minimum power curve, average power curve and the maximum power curve. These projected curves were projected based on the evaluation of long-term wind velocity and direction measurement and supplied power. The right-hand part shows three diagrams, in the first of them there is predicted wind velocity for forecast for next three days. The centre diagram shows the predicted power with already made corrections. The bottom column diagram shows predicted electric power produced. The display for various options can be changed by means of the taskbars on the right side. This enables displaying predicted values

for one wind power plant, for wind plants in one region or all power plants if the Czech Republic. The results shown on the right side of Fig. 2 can be displayed by means of diagrams or tables, to switch between them the bottom taskbars serve. Similarly through the left-bottom taskbars the information on a monitored wind plant can be switched. Information on a wind power plant can be displayed as well as measured power curves and the power curve supplied by the manufacturer of the wind plant.

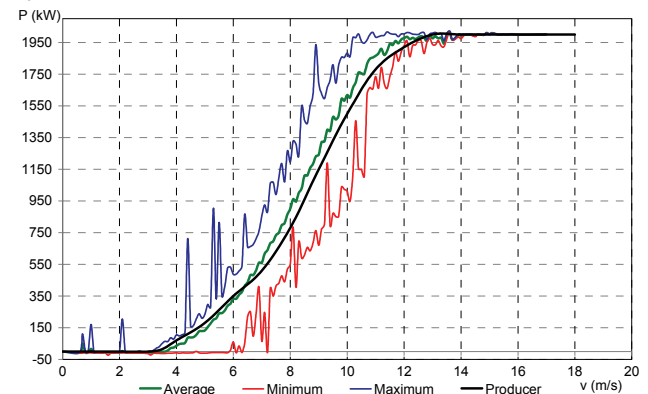


Fig.3. Power curve of a 2MW wind power station

The verification of a prediction model

As it was mentioned above, a prediction model of WPS electricity generation is being carried out at the VSB-TU Ostrava as part of a research target [11]. The functionality of a mathematical prediction model being developed is made concrete for the operation of a 2MW wind power station in the North-Moravian Region. The wind power station is equipped with a 2MW, 690 V asynchronous generator with a slip-ring armature in cascade configuration employing a frequency converter. One of the key parameters defining the efficiency of the conversion of wind energy to electrical energy. As per the power curve the electrical power is specified for a concrete type of wind power station at the station threshold for given wind velocity. Figure 3 shows the power curve of the analyzed 2MW wind power station. The figure clearly shows a WPS initial level at wind velocity 3 ms^{-1} , then velocity gradually increases while the output power grows in a linear way up to 12 ms^{-1} when the mechanical power is limited by turning wind motor vanes. The wind station power curve shown has been designed based on the database of measured power flow values and meteorological data. And just the dependence of electrical output power on wind velocity at the height of wind motor hub is employed for calculating the prediction value of wind station electricity. The calculation algorithm is as follows:

1. creating a database of predicted wind velocity using mathematical prediction models (specifically the WRF model is applied),
2. correcting predicted wind velocity for a given location and parameters of a specific 2MW wind power plant,
3. sensitivity analysis of correction factors,
4. calculate the predicted power in a given time horizon,
5. time integration of predicted power in order to get the required value of disposable energy from the wind power plant.

Correction of wind velocity prediction

Let's suppose that we have given sequence of wind velocities $v^m_1, v^m_2, \dots, v^m_n$ and azimuths $\omega_1, \omega_2, \dots, \omega_n$ for $n \in \mathbb{N}$, that were measured at location of WPS of some period of time. Let's also suppose, that we have given corresponding predicted wind velocities $v^p_1, v^p_2, \dots, v^p_n$ that

were predicted by some of meteorological model¹. Our task from mathematical point of view is to create the third sequence of wind velocities $v_1^c, v_2^c, \dots, v_n^c$, where some correction are taken into account.

Table 1. Exponent α versus kind of surface, [13]

Kind of Earth's surface	α
Smooth surface – water level, sand	0.14
Grass field with low grassy vegetation or plough	0.16
High grassy, grain vegetation	0.18
High vegetation of arable crops	0.21
Woods	0.28
Villages and small cities	0.48

To measure quality of correction process two error function are defined:

$$(1) \quad err_{m,c} = \sqrt{\sum_{i=1}^n (v_i^m - v_i^c)^2}$$

$$(2) \quad err_{m,p} = \sqrt{\sum_{i=1}^n (v_i^m - v_i^p)^2}$$

If correction process improves the quality of wind velocity prediction, then $err_{m,c} < err_{m,p}$.

The wind velocity correction considering the height of the WPS hub

The hub height of wind stations is continuously growing together with the power of wind power stations. Wind velocity is influenced by earth surface and generally decreases in the closest distance to it. That is why it is necessary to make a correction of wind velocity from the prediction model to the one in the hub height. In vast majority of cases, prediction models predict wind velocities for the height of 10 meters above ground. However, today's modern wind power stations reach the height of 90 to 100 meters, off-shore power stations located at sea level are even higher. According to [13] we can write the height correction as:

$$(3) \quad v_i^c = v_i^p \left(\frac{H}{H_o} \right)^\alpha$$

where H is the height of wind turbine over Earth's surface and H₀ is referential height, current value H₀ = 10 m. The correction correlation index α depends on surface roughness. In [4] the bottom limit $\alpha = 1/7$ is stated, common value $\alpha = 0.25$ and maximum value $\alpha = 0.426$. Common values of exponent α are provided in Table 1.

The wind velocity correction considering wind direction

The terrain in the WPS surrounding is mostly broken, the wind blowing in the WPS direction from different directions has to overcome various obstacles and from different directions it will be slowing down due to different surfaces. Then azimuth correction can be expressed as the function $\beta : R \rightarrow R$, which assigns a certain correction coefficient to each azimuth ω_i , where $0 \leq \omega_i \leq 2\pi$. Thus the formula for wind velocity correction can be expressed, using Eq. (3), as follows:

$$(4) \quad v_i^c = v_i^p \beta(\omega_i) \left(\frac{H}{H_o} \right)^\alpha$$

For practical purposes it is some approximation of function $\beta(\omega_i)$ is sufficient. In the used prediction model the full angle is split in 16 parts and azimuth is uniformly quantized with step $\Delta = \frac{2\pi}{16}$. Let's define quantization

function $q : R \rightarrow \{1, 2, \dots, 16\}$ as:

$$(5) \quad q(\omega_i) = \begin{cases} 1 & \text{for } 0 \leq \omega_i < \Delta \\ 2 & \text{for } \Delta \leq \omega_i < 2\Delta \\ \dots & \dots \\ \dots & \dots \\ 16 & \text{for } 15\Delta \leq \omega_i < 16\Delta \end{cases}$$

The function $\beta(\omega_i)$ is discretized into sixteen values $\beta_1, \beta_2, \dots, \beta_{16} \in R$ as

$$(6) \quad \beta(\omega_i) \approx \beta_q(\omega_i)$$

Solution Using System of Linear Equations

Given n measured velocities and n predicted velocities, the n equations with seventeen unknowns can be written using Eqs. (4) and (6). Usually this system of equations is overdetermined, thus only approximation of solution can be computed. Formally we obtain:

$$(7) \quad \log v_i^c = \log v_i^p + \log \beta_{q(\omega_i)} + \alpha \log \left(\frac{H}{H_o} \right)$$

and then

$$(8) \quad \alpha \log \left(\frac{H}{H_o} \right) + \log \beta_{q(\omega_i)} = \log \left(\frac{v_i^c}{\log v_i^p} \right)$$

where α and $\log \beta_{q(\omega_i)}$ are unknowns. Such system of equations can be solved using least square method.

Solution Using Multidimensional Optimization

The problem of finding the values of coefficients $\alpha, \beta_1, \beta_2, \dots, \beta_{16}$ can also be formulated as the optimization problem. Error function, see Eq. (1), can be rewritten using Eqs. (4) and (6) as follows:

$$(9) \quad err_{m,c} = \sqrt{\sum_{i=1}^n \left[v_i^m - v_i^p \beta_{q(\omega_i)} \left(\frac{H}{H_o} \right)^\alpha \right]^2}$$

The problem consists in finding the minimum of the function $err_{m,c}$ for these seventeen variables $\alpha, \beta_1, \beta_2, \dots, \beta_{16}$. We have applied for the calculation the Powell's conjugate gradient method [9]. The advantage of this method, as compared to other gradient optimization methods, is that it does not require the calculation of minimized function gradient.

Feedforward Neural Network Approach

A feedforward neural network is an artificial neural network (ANN) where connections between the neurons do not form a directed cycle, i.e. the network forms directed acyclic graph. The feedforward neural network was

proposed by Rosenblatt in 1958 [12]. The feedforward neural network is also known as the perceptron. The feedforward neural network works by having one or more hidden layers sandwiched between an input and output layer, see Fig. 4.

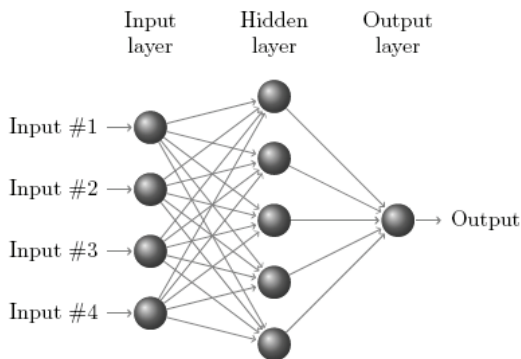


Fig. 4. Feedforward Neural Network

There are n_{inp} neurons in input layer, n_{hi} neurons in i -th hidden layer and only one neuron in output layer. Input data are passed to input layer neuron and using synapse they are transmitted into output neuron. In case of wind velocity prediction output feedforward neural networks computes v_i from k previous predicted velocities $v_1^p, v_2^p, \dots, v_{i-k}^p$. In other words k represents left context of current predicted velocity and neural network is trained to predict wind velocity from these predicted velocities that is close to measured velocity as much as possible. Formally, the goal of neural network training is to minimize error function given by Eq. (1).

Experimental Results

Measured and predicted wind velocities from WPS at Veselí na Moravě from June 2008 were used as a source for our experiments. All three method of velocity correction were tested on this data. Values error function were also computed. The error function $err_{m,p} = 65.564$ is common for all experiments and it represents the threshold for comparison of our success in velocity correction.

Now we can analyze result of above mentioned three methods:

- The least squares method provides, according Eq. 8, correction coefficient presented in Table 2. In this case, it is apparent that the solution result is not in compliance with expected values presented in Table 1. The error function has value $err_{m,c} = 55.157$.
- On the other hand, the result obtained using the Powell's method is more in accordance with expected values, see Table 2. The value of error function is also smaller $err_{m,c} = 50.088$. As you can see, both methods have improved velocity prediction, but only very limited.
- As it was mentioned in Sect. feedforward neural network consists of input, several hidden layers and output layer. The size of output layer is clear – one neuron. The size of all other layers should be estimated experimentally, but it must be kept in reasonable bounds. We can suppose, that left context up to 24 hours is enough for wind velocity prediction. Another issue is the number of hidden layers. Four neural networks with different topologies were tested in our experiments. The results of these experiments are given in Table 3. The best result was obtained for network with 24 neurons in input layer, and two hidden layers with 48 and 24 neurons respectively.

Table 2. Correction Coefficients

Coefficient	Least Square Method	Powell's Conjugate Gradient Method
α	-0.318	0.194
β_1	3.588	1.206
β_2	3.051	0.962
β_3	2.524	0.825
β_4	3.602	0.785
β_5	5.651	2.002
β_6	7.962	2.807
β_7	6.436	2.054
β_8	6.523	1.524
β_9	5.365	1.104
β_{10}	3.731	1.120
β_{11}	3.449	1.086
β_{12}	3.402	1.093
β_{13}	3.312	1.040
β_{14}	4.002	1.125
β_{15}	5.158	1.457
β_{16}	3.247	1.116

Table 3. Parameters of Tested Neutral Networks

	# of Neurons			
Input Layer	12	12	24	24
Hidden Layer 1	24	24	48	48
Hidden Layer 2	0	12	0	24
Output Layer	1	1	1	1
$err_{m,c}$	31.643	19.586	18.243	1.538

Graphical representations of measured wind velocity and predicted velocity with correction for all three methods of correction are shown in Fig. 5. There are clearly visible differences among measured velocity and corrected velocity in case of least square and multidimensional optimization methods. Only feedforward neural network correct wind velocity with high accuracy. To clarify the success rate of all correction methods, we can draw graph with error curves i.e. difference between measured velocity and corrected velocity, and for comparison difference between measured and predicted velocity without any correction. The error curves are shown in Fig. 6. There are three highly fluctuating curves and one nearly constant curve – error of correction using feedforward neural network in the best case, see Table 3.

Conclusion

Results prediction of output power from wind power plants are shown in this paper. The model was developed in the Technical university of Ostrava and its algorithm is based on knowledge's of weather forecast and power curve of predicted wind power plant. The validity of model was verified within real experiment at wind power plant 2 MW for long time interval. Real experiments were accomplished for obtaining database with data about velocity and direct of wind and power flows. These data were used as a basis for verification of validity of prediction models. It is needful to define some correction method to improve prediction of wind power. The purpose of the correction is adopting of prediction to local another wind power plants in the Czech Republic is assumed to the next in the future. condition of individual power station. We propose three correction methods. The first two method have analytic character. They are based on solving of system of equations using least square method or Powel conjugate gradient method. The third one is based on artificial neural network. The

experiments show that neural network outperforms remaining two methods. Expansion of predictive model application to another wind power plants in the Czech Republic is assumed to the next in the future.

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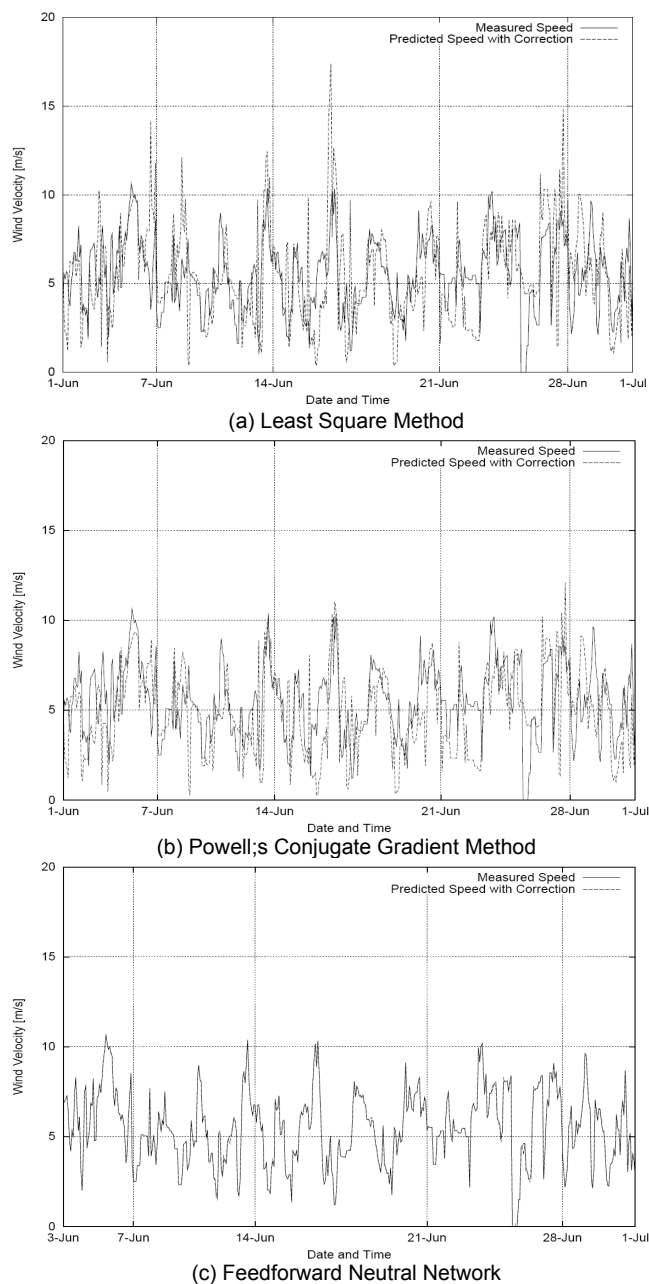


Fig. 5. Comparison of measured and corrected wind velocity

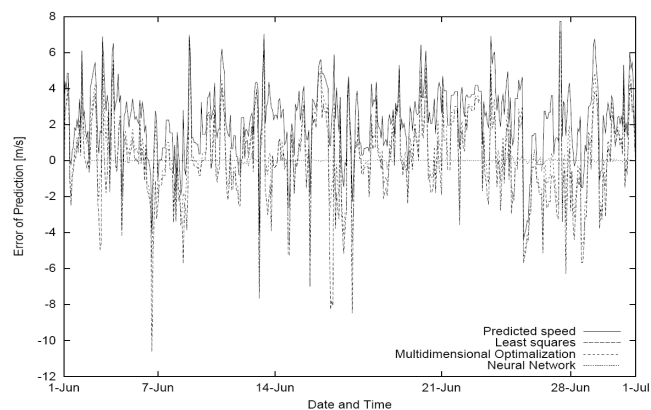


Fig. 6. Errors in velocity correction