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NEURAL MODEL OF A WIND TURBINE

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Abstract – The paper presents a neural model, based on a GMDH neural network, used for modelling the power generated by a wind turbine. The research results of this model are presented compared to the research results of two stochastic models (WPPT and GWPPT). The presented statistical evaluation of three models shows that the most preferred model for the power generated by a wind turbine is a GMDH neural model.

Keywords: wind turbine, neural networks, predicting.

1. INTRODUCTION

In the past, electricity has been harvested from fossil energy sources, mostly. As power *demand* is comparably easy to predict, power *supply* from fossil sources is almost deterministic. However, for renewable energy sources like wind power or solar power, energy supply is strongly stochastic and hard to predict, since wind power depends on wind speed and solar power depends on coverage; in short, renewable electricity supply depends on weather, which is hard to predict.

The proper functioning of the energy system requires information about the planned delivery of electricity from wind farms. This requires the development and build of an appropriate control-measuring system, in which an important element is the module for predicting the value of generated electricity by a wind farm with 72 hours horizon. Hence, the purpose of this article is to present the results of studies on prognostic models.

In the short-term scenario, wind power predictions of up to 12 hours are required for market clearing at the electricity pools and for network dispatching. Therefore, there is a wide range of predicting model propositions available in the literature. Most approaches for the short-term predicting horizon are based on stochastic modelling. One of the most successful ones is WPPT (Wind Power Prediction Tool) [1]. WPPT and its recent generalization – GWPPT (Generalized Wind Power Prediction Tool) [2] – are state-of-the-art models and are broadly implemented in the industry.

In this paper we suggest a new model that does not depend on stochastic approaches but uses a new kind of neural network modelling. With in-sample-predictions we are able to show that our new approach outperforms the WPPT and the GWPPT benchmark models by a severe degree.

The paper is structured as follows: Section 2 presents the WPPT, the GWPPT and the new model's basic principles. Section 3 presents the research results of the three models. Section 4 presents the statistical evaluation of the models. Section 5 provides a short conclusion.

2. MODEL OVERVIEW

Here, we provide an introductory discussion of WPPT, GWPPT and the neural network model based on GMDH neural network. For GMDH neural network model a commercial tool GMDH Shell was used.

2.1. WPPT

WPPT is a dynamic regression model. Wind power is the dependent variable, while the explanatory variables are wind speed and time. Time is introduced into the model by means of four Fourier series terms that capture the diurnal periodicity of wind power. The model equation is

$$\begin{aligned}\hat{x}_{t+k} &= m + a_1 x_t + a_2 x_{t-1} + b_1 w_{t+k|t} + b_2 w_{t+k|t}^2 + \\ &d_1^c \cos\left(\frac{2\pi d_{t+k}}{144}\right) + d_2^c \cos\left(\frac{4\pi d_{t+k}}{144}\right) + \\ &d_1^s \cos\left(\frac{2\pi d_{t+k}}{144}\right) + d_2^s \cos\left(\frac{4\pi d_{t+k}}{144}\right) + \varepsilon_{t+k},\end{aligned} \tag{1}$$

where x_t is wind power at time t, $w_{t+k|t}$ is wind speed at time $t+k$ as provided at time t, d_t is daytime at period t and ε_{t+k} is assumed white noise.

2.2. GWPPT

The generalized model introduces wind direction as an additional explanatory variable and also exploits an a-priori known information: The power range of the turbine. Provided that the turbine cannot produce less than zero power and has a strictly defined upper limit (which is the case for all modern turbines), there are well defined limits l (*lower*, usually zero) and u (*upper* limit).

For GWPPT, equation (1) is expanded by a term for wind direction and it is assumed that

$$x_t = \begin{cases} l, x_t^* \le l \\ x_t^*, x_t^* \in (l,u) \\ u, x_t^* \ge u, \end{cases} \quad (2)$$

where x_t^* are the empirically observed wind power information. The parameters are estimated by a generalized Tobit ML (Maximum Likelihood) procedure, as errors are assumed to be Gaussian. Post regression, the power is calculated by the conditional mean

$$\hat{x}_{t+k} = (\Phi(f_2) - \Phi(f_1))x_{t+k}^* + (\phi(f_2) - \phi(f_1))\hat{\sigma} + u(1 - \Phi(f_2)), \quad (3)$$

where

$$f_1 = \frac{l - x_{t+k}^*}{\hat{\sigma}}, \quad (4)$$

$$f_2 = \frac{u - x_{t+k}^*}{\hat{\sigma}}, \quad (5)$$

and $\phi(\bullet)$ and $\Phi(\bullet)$ are normal PDF (*Probability Density Function*) and CDF (*Cumulative Distribution Function*).

2.3. GMDH

The methods presented above are based on stochastic models. In situations where there is a partial or total lack of knowledge of the rules that describe objects or processes, resulting in a large complexity of problems, neural networks (NN) can be used. They enable the creation of behavioural models, the operation of which corresponds to the behaviour of these objects and processes. An example of such an object is a wind turbine, wherein the values of generated power depend not only on the speed and direction (azimuth) of the wind. The result of generated power is also influenced randomly by the dynamics of work of the mechanical components of a wind turbine. The result is that for the same parameters of the wind a different value of generated power is produced. NN has an ability to build models with a method based solely on the analysis of specific data, i.e., the inductive method. NN are powerful mathematical tools used to solve non-linear problems [3-5].

Modelling objects and processes using NN requires a training process of a NN. Achieving the best possible accuracy of training of the network with traditional neural networks, such as MLP (*Multilayer Perceptron*) requires a selection of the number of hidden layers of the network, as well as the number of neurons in these layers. An incorrect selection of the NN structure can increase the values of the errors in the training and predicting process.

The solution to this problem is the use of a self-organizing NN, such as GMDH networks (*Group Method of Data Handling*) [6]. The GMDH network structure is formed automatically on the basis of prepared training and testing sets of data. In the course of the training process, the network expands and evolves until the enhanced efficiency of its operation has been achieved [6]. Before a new layer of neurons is attached to the current structure of the network, elements of the new layer are subjected to selection for accuracy of processing. Neurons that do not meet the criterion for assessing the condition imposed, i.e., the processing error is too large, are eliminated from the structure of the network. In the training process the parameters of polynomial defining the activation function of each neuron are estimated. The quality of NN training process depends on the number of training data and method of its preparation.

3. RESEARCH RESULTS

The values of parameters of stochastic models (WPPT and GWPPT) and the neural model GMDH-NM (based on the GMDH NN) for modelling the power generated by a wind turbine is established on the basis of historical measurement data characterizing the actual work of a wind turbine with a power of 2000 kW (Fig. 1).

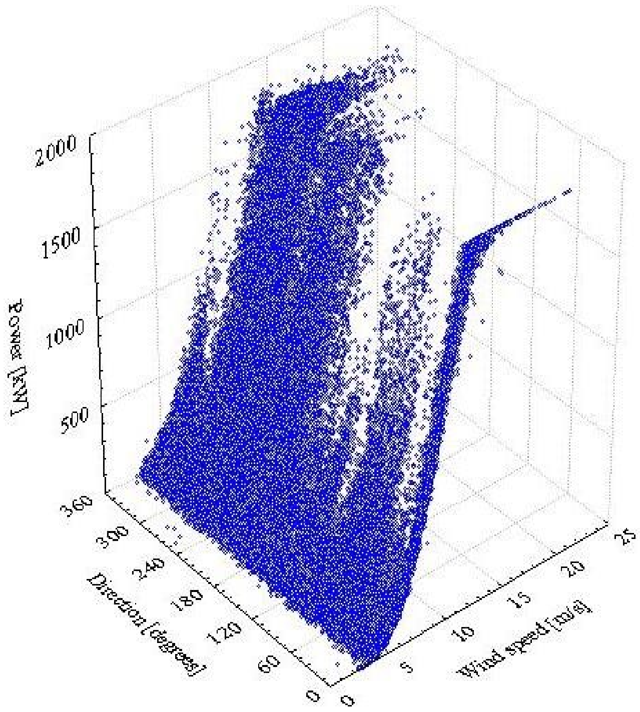

Fig. 1. The dependence of the power generated by the wind turbine from the wind speed and direction.

In the case of the GMDH-NM model, to determine its structure and parameters in the training process, a training data set consisting of about 65000 vectors is used. Each vector contains three elements, which values are the wind speed, azimuth and the corresponding value of power generated by a wind turbine. These data are known at an interval of 10 minutes.

Based on the three models defined above, the power that a wind turbine will generate is modelled at a horizon of 72 steps (12 hours). The study of these models is carried out on the basis of historical values of parameters of wind (speed and azimuth), which is fed into the input of the models. The results of modelled power generated by a wind turbine (P_{Model}) are compared to the actual values of generated power ($P_{Turbine}$) for the same input parameters. For each model, 3927 modelled power are designated, corresponding to about 28 days of data, with 10 minutes interval.

The results of modelled power based on WPPT, GWPPT and GMDH-NM models are presented in Fig. 2, 3 and 4.

4. EVALUATION OF THE MODELS

Research results presented in Fig. 2, 3 and 4 indicate that modelled power based on the WPPT model is carried out with the greatest errors. The WPPT model provides very large negative values of modelled power.

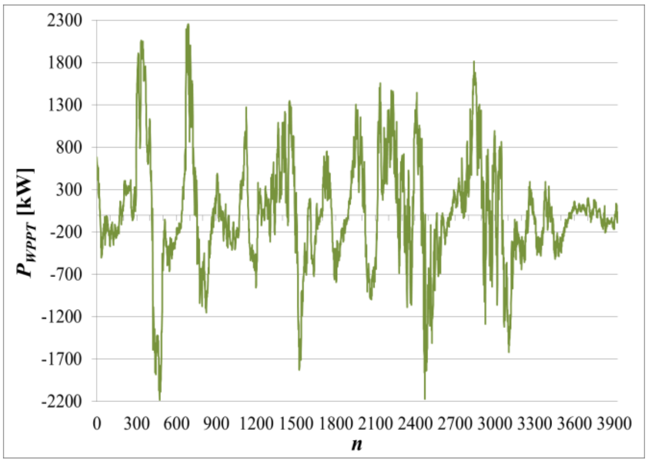

Fig. 2. The results of generated power obtained by WPPT model, where n is a number of modelled value.

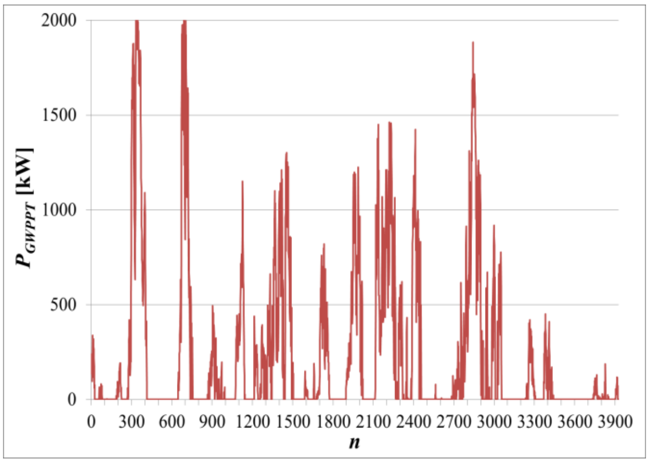

Fig. 3. The results of generated power obtained by GWPPT model, where n is a number of modelled value.

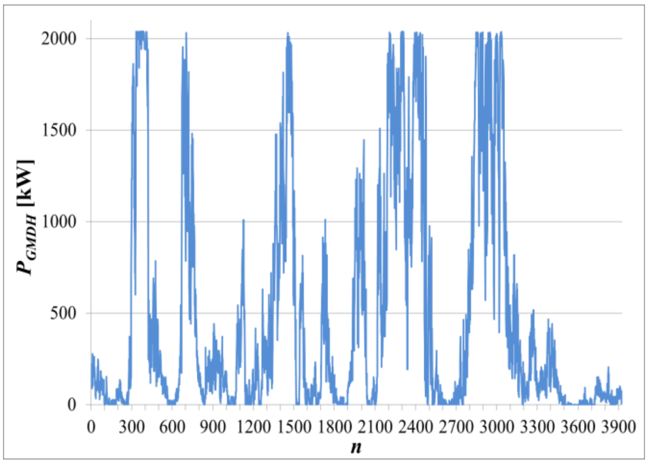

Fig. 4. The results of generated power obtained by GMDH-NM model, where n is a number of modelled value.

The values of obtained residuals for three models are presented in Fig. 5, 6 and 7.

The statistical evaluation of these models is based on the calculated values of residuals

$$r(t) = P_{Turbine}(t) - P_{Model}(t). \tag{6}$$

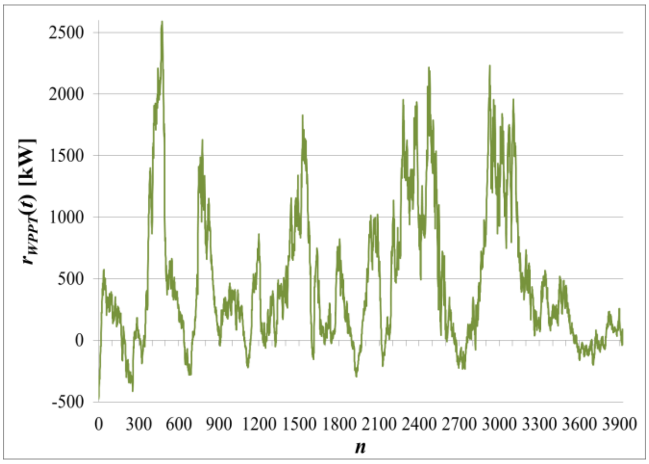

Fig. 5. The residuals r obtained by WPPT model, where n is a number of modelled value.

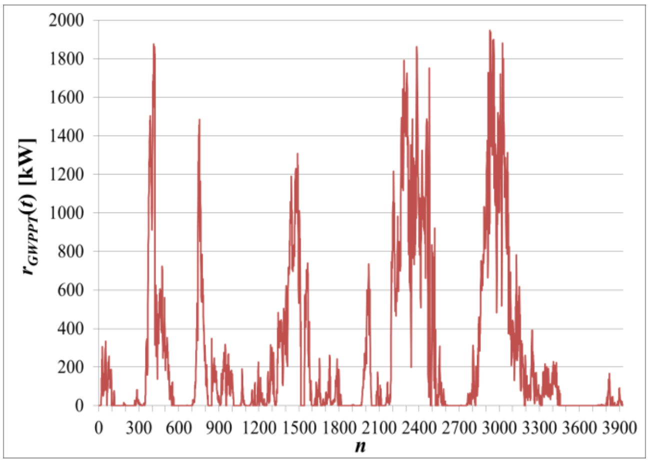

Fig. 6. The residuals r obtained by GWPPT model, where n is a number of modelled value.

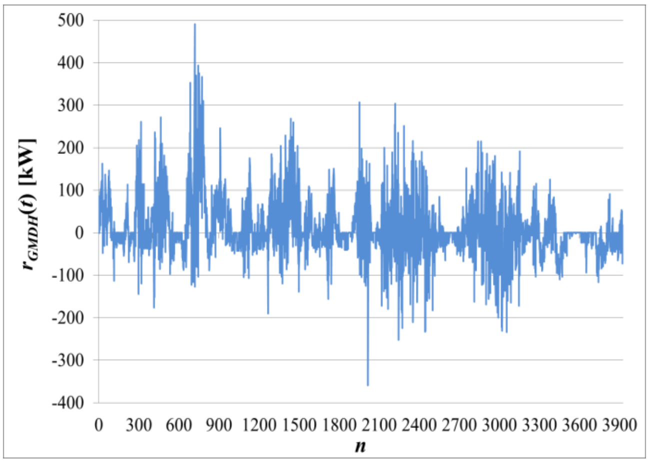

Fig. 7. The residuals r obtained by GMDH-NM model, where n is a number of modelled value.

The determined r residuals are the basis for the evaluation of the quality of the developed models. Minimum (*min*) and maximum (*max*) values of the residuals are determined. However, from the group of many measures used for evaluation of the quality of models [7], the following errors are used: Mean Error (*ME*), Mean Absolute Error (*MAE*), Mean Squared Error (*MSE*), Root Mean Squared Error (*RMSE*), Thiel coefficient (I^2) and coefficient of Pearson's linear correlation ($cor_{P_{Turbine},P_{Model}}$) between $P_{Turbine}$ and P_{Model} values. Also, values of three components of Theil coefficient I_1^2, I_2^2, I_3^2 and relative values of these components (U_1, U_2, U_3) are calculated, which determine the cause of the generation of errors of modelling. The I_1^2 component represent the prediction load, I_2^2 is associated with insufficient flexibility of the prediction, so the inaccuracy of estimating the expected volatility of the variable of prediction and I_3^2 reports of an error related to the insufficient compliance of a change in prediction direction with a change in direction of predicted value.

Table 1 shows the results of calculations of the *max* and *min* values of residuals and the values of selected measures of quality of models.

Table 1. Values of measures of quality of modelling.

Measures of quality	Models		
	GMDH-NM	GWPPT	WPPT
max r [kW]	491	1947	2591
min r [kW]	-359	0	-477
ME [kW]	10.4	263.2	469.7
MAE [kW^2]	43.9	263.2	511.5
MSE [kW^2]	4421	248019	541038
RMSE [kW]	66.5	498	736
$cor_{P_{Turbine},P_{Model}}$	0.995	0.751	0.615
I^2	0.0069	0.3874	0.845
I_1^2	0.00017	0.1082	0.345
I_2^2	0.00008	0.07616	0.0008
I_3^2	0.00665	0.20300	0.4997
U_1 [%]	2.46	27.94244	40,82840
U_2 [%]	1.17837	19.65878	0.09467
U_3 [%]	96.36163	52.39878	59.13609

The results clearly show that the proposed GMDH-NM outperforms the WPPT and GWPPT models, as shown by the calculated values of measures of quality of model. Each of calculated values of measures used for evaluation of the quality of the developed model are smaller for GMDH-NM model than for WPPT and GWPPT models. The comparison of the *ME* and *MAE* errors and the value of component of I_1^2 coefficient between the GMDH-NM model and GWPPT model indicates that the smaller load of prediction is for the GMDH-NM model. This means that the applied GMDH-NM model has good properties. For GWPPT model the obtained values of modelled power are overestimated (only positive values of residuals). Also, the other components of Theil coefficient I_2^2, I_3^2 are definitely worse for GWPPT model. For the GMDH-NM the values of coefficient I_2^2, I_3^2 are respectively 0.00008 and 0.00665, and in the case of GWPPT model respectively 0.07616 and 0.20300. This means that for GWPPT model there is an inaccuracy of estimating the expected volatility of the variable of the model, and also the insufficient compliance of a change in model direction with a change of modelled value. Very small value of I_2^2 and U_2 for GMDH-NM means that the volatility of the modelled values is good relative to the volatility of the observed values. Also the value of Pearson's linear correlation shows superiority of the GMDH-NM over the GWPPT and WPPT models. The value of 0.995 for GMDH-NM shows very broad convergence between modeled power and power generated by the turbine. However for each of the analyzed cases relative value of U_3 of the I^2 reached the highest values. This means that the biggest part of I^2 error has I_3^2 component that is associated with inadequate compliance of a change in model direction with a change of modelled value.

5. CONCLUSIONS

The obtained research results and their statistical analysis confirm the possibility of using neural networks for modelling the power generated by a wind turbine. The proposed GMDH-NM model enables to receive much better results of modelled power generated by a wind turbine in relation to the GWPPT and WPPT models.

A valuable advantage of the GMDH neural network is its automatic adjustment of the structure to the actual operating parameters of the wind turbine. It also allows to receive values of modelled power generated by a wind turbine in short period of time.

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