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LITHUANIAN ENERGY INSTITUTE

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INVESTIGATION OF FACTORS DETERMINING WIND POWER PREDICTION ACCURACY

Summary of Doctoral Dissertation
Energetics and Power Engineering (06T)

2018, Kaunas

The scientific work carried out in 2013 – 2017 at Lithuanian Energy Institute, Laboratory for Renewable Energy and Energy Efficiency. The studies were supported by Research Council of Lithuania.

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TABLE OF CONTENTS

INTRODUCTION

Wind energy is one of the fastest developing renewable energy sectors in the world and in Lithuania. 511 MW of wind power were installed in 2017. However, such rapid development of wind turbines requires analysis of the possibilities to connect wind farms to the national grid and more detailed estimation of wind potential. Besides, wind power development is typically a challenge for the grid operator because it causes issues of grid balance and requires reserves. The solutions of this kind of problems are wind power prediction systems and improvement of their accuracy.

Several main types of models are used for wind power prediction: time series, statistical and physical models. Also, combined hybrid models can be used which have been proven as giving the best forecast results. These models and forecasts are used to predict the wind power output of a stand-alone wind turbine or a wind farm. From various terms and categorizations of the prediction horizon, which may be found in literature, there are three typical prediction horizons used: very short-term – from several seconds to 1 hour, used for wind farm operation control, short-term – 6 hours, midterm – 6-48 h, used for load determination and planning in advance, electricity market, cost optimization, and long term (from 48 h to weeks), used for planning of wind farm maintenance works and allocation of other power generation sources.

Despite huge number of models and improvements in wind power forecasting methods, wind power forecasts still suffer from relatively high errors, depending on several factors, such as forecasting horizon, type of forecasting model, size of wind farm and geographic location. Also, wind power prediction errors depend on local topographical and wind conditions. As a result of this, it is very important to analyse wind conditions, the dependence of power forecasting errors on local topographical characteristics, and to find the best suitable methods for more accurate wind power forecasting. It enables facilitation of wind turbines integration into the power system in order to achieve the strategic goals set by European Union and Lithuania.

Aim of the Doctoral Dissertation

To investigate factors determining wind power prediction accuracy and to create a new hybrid method with increased wind power prediction accuracy.

Tasks of the work

1. To identify the best suitable methods for the wind speed distribution approximation during different wind conditions.
2. To analyse influence of topographical conditions and wind characteristics on wind power prediction accuracy.
3. To determine the most accurate functions for the approximation of the power curves for wind turbines.
4. To identify the best suitable statistical methods for wind power forecasting.
5. To create new hybrid method for more accurate wind speed and wind power prediction.

Scientific novelty of the work

A new hybrid wind power prediction methodology with detailed complex evaluation of topographic and wind conditions is proposed.

Practical value of the work

A new hybrid model for long-term and midterm wind power prediction was developed. Model can be used for wind resource estimation and for more accurate wind turbine or wind farm power forecasting, in order to reduce power system balancing, control and exploitation costs.

Statements presented for defence

- The best suitable tools for the wind speed distribution approximation are Rayleigh's and WAsP methods.
- Detailed evaluation of local topographical conditions allows to reduce wind power prediction errors.
- Intensity of wind characteristics do not have direct relation with wind power forecasting errors.
- Identification of the most suitable statistical methods improves wind power forecasting accuracy.
- Combination of statistical and physical methods is the best choice to reduce wind power prediction errors.

Approval of the work

The material of the doctoral dissertation has been published in 2 articles in journals included in “Clarivate Analytics Web of Science” database, and 2 papers in journals registered in international databases. The material of the dissertation has also been presented in 6 international scientific conferences, 2 of them took place abroad.

Structure of the dissertation

The dissertation consists of introduction, 3 chapters, conclusions and a list of references. The dissertation is compiled of 100 pages, including 53 figures and 25 tables. The list of references has 122 items.

1. LITERATURE REVIEW

1.1. Wind speed and power prediction methods

Global power consumption grew very rapidly during the last 15 years, and it is forecasted that it will grow in the future as well, because new power generation plants are necessary to meet increasing energy demands in the world and in Lithuania. To compare, 24.5 GW capacity of new power plants were built across the European Union in 2016, and renewables made 86% of that (Wetstone et al., 2016). Wind energy is the most rapidly developing kind of renewable energy in the world. However, wind power dependence on the wind volatility is one of the most important issues compared to the traditional power generation. It complicates the task of grid balancing (Jónsson et al., 2010; Ketterer, 2014). This situation requires wind speed and power prediction systems, which are already used in a number of wind power developing countries to facilitate the power balancing of the system. Therefore, with increasing wind power share, more precise wind power prediction methods are becoming necessary for successful integration of wind power (Grassi et al., 2012; Park et al., 2015; Zhao et al., 2012).

Wind power prediction methods can be separated into two different approaches. One of them is statistical methods and the second one – physical power prediction methods (Fig. 1.1) (Wang et al., 2016). The first group covers methods related to historical relations between variables, and they are most suitable for short-term power prediction. The second group – physical approach methods – are based on wind prediction from numerical weather forecasting system, when the wind speed is corrected according to the local conditions and converted to wind power (Fan et al., 2015; Zhang et al., 2014). Besides, hybrid models, which integrate statistical and physical methods exist as well. But there is still a lack of very careful evaluation of meteorological and topographic conditions such as orography, roughness, wind shear and turbulence impact on the accuracy of wind power prediction (Gallego-Castillo et al., 2015; Lei et al., 2009; McAuliffe et al., 2012; Singh et al., 2009). The project presents analysis of influence of local topographic conditions and statistical methods, and also indicates best tools for short, mid- and long-term wind power forecasting.

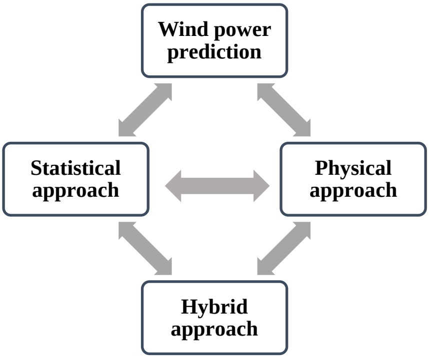

Fig. 1.1. Wind power prediction methods (Lei et al., 2009)

There are plenty of models used in the world for wind power prediction and the truth is that there is no single best model for all cases because wind speed variations are different in various geographic locations and efficiency of wind speed conversion to power varies among different wind turbine manufacturers. The main source of wind power prediction inaccuracies are the numerical wind prediction models. Another source of errors comes from the wind power conversion stage, i.e. wind turbine power curve model used (Fig. 1.2) (Giebel, 2011; Wang et al., 2011).

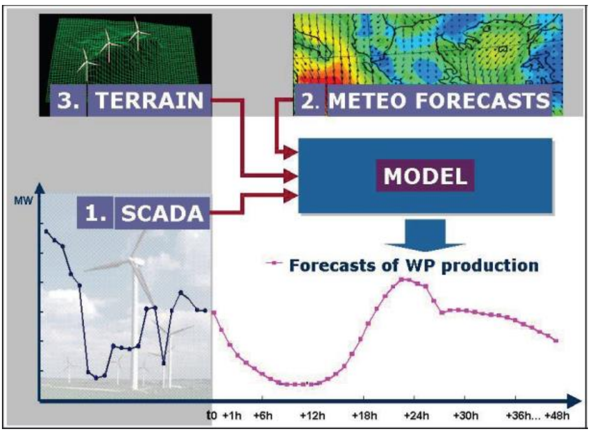

Fig. 1.2. The various forecasting approaches can be classified according to the type of data input (Giebel, 2011)

Despite improvements of wind power prediction models, annual wind power prediction error reaches 7-8% in the world and in Lithuania (Matelionis, 2016). To decrease the inaccuracy of power prediction it is necessary to analyse power forecasting at different heights, choose optimal parameters, assess the most suitable methods for approximation of the wind power curves and research adoption of model output statistics for wind power prediction (Androulidakis et al., 2015; Foley et al., 2012; Zhu et al., 2012).

1.2. Influence of topography and wind conditions on power forecasting

As it was mentioned before, wind speed variations are closely dependent on topographical and wind characteristics. To explain the influence of topographical factors on wind power prediction process, the boundary layer should be analysed (Olaofe et al., 2013). The wind flows are exposed to topographical conditions, such as surface, buildings, forest and so on. Moreover, thermal friction between boundary and higher atmospheric layers also generates turbulence. Because of that there is no linear relation between wind characteristics and power prediction errors (An et al., 2013; Jiang et al., 2011; Li et al., 2014).

The influence of surface roughness on wind speed profile can be described in the following manner: in the beginning, roughness (trees) create internal boundary layer; later, considering the obstacles, internal boundary layer is changing again and every obstacle reduces wind speed, which can be estimated as sum wind speed and shear coefficient (Kim et al., 2017a; Troen et al., 1989).

Considering topographical conditions, one of the most important parts is relief. Relief variations influence wind speed changes. Wind speed changes regarding relief variations (increasing height of relief) can be described in the following manner: in the first step, wind speed decreases and wind profile changes, later wind profile is constant. Finally, on the top of the hill, wind speed increases very rapidly and wind profile changes very fast (Kim et al., 2017a).

Because of that the variations of wind speed are very significant, and it is important to estimate wind speed changes in terms of relief variations. Detailed evaluation of topographical conditions enables to increase the accuracy of power prediction (Kim et al., 2017b; Sun et al., 2017).

1.3. Power curves modelling and statistical power prediction methods

The conversion process of wind speed to wind power by wind turbine power curve is one of the key steps for accurate wind power prediction. Many different techniques are used for modelling power curves. However, there are still huge approximation errors. The most typical mathematical functions for nonlinear power curve modelling are polynomial power curves (Chang et al., 2014; Pelletier et al., 2016). Other commonly used methods are exponential power curve, cubic power curve, as well as modified hyperbolic tangent (MHTan) function (Fig. 1.3), logistic function and neural network approach (Carrillo et al., 2013; Lydia et al., 2014; Thapar et al., 2011) .

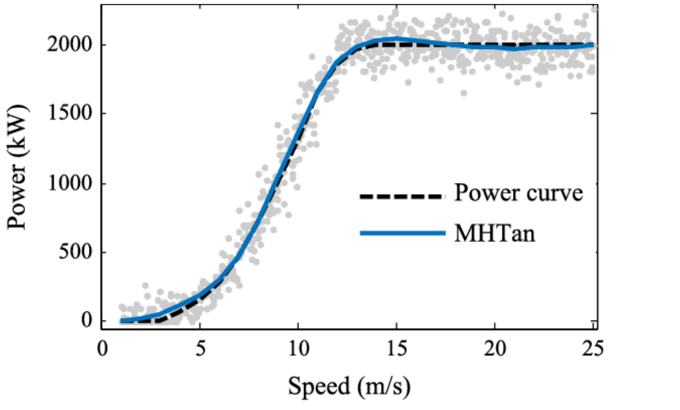

Fig. 1.3. Example of wind turbine power curve modelling (Taslimi-renani et al., 2016)

According to Carrillo et al. (Carrillo et al., 2013), exponential and cubic approximations give higher coefficient of determination (R^2) values and lower error in energy estimation. In the approximation of cubic power curve, high values of R^2 and low errors in energy estimation were presented. However, the polynomial power curve shows the worst results mainly due to its sensitivity to the data given by the manufacturer.

Review of the power curve models has revealed that most models are complex, having many parameters to be estimated, dependent on several factors, which require the application of multiple regression method or non-parametric techniques. Nevertheless, most of them do not fit physical properties of power curve, i.e. they exceed the maximum generated power of a particular wind turbine, for instance, widely used polynomial or MHTan functions (Jiang et al., 2015; Jung et al., 2014; Zolfaghari et al., 2015).

Statistical methods group for wind power prediction covers equations related to factual and predicted data during period. They are best suitable for short-term power prediction (Pinson et al., 2008). Most of them are auto regression functions (1.1 equation), where relations between numbers are used. One of the most popular is auto regression function, moving average function as well or both functions including method, it calls ARMA (1.2 equation). Besides, it can be option, when integrated moving average function is included and it calls ARIMA (2.12 equation) (Chen et al., 2014; Stathopoulos et al., 2013; Zhao et al., 2011).

$$x_t = \sum_{i=1}^{p} \varphi_i x_{t-i} + \varepsilon_t; \tag{1.1}$$

where: x_{t-i} –factual power (kW), x_t – predicted power (kW), ε_t – error (kW).

$$x_t = \mu + \varepsilon_t + \sum_{i=1}^{p} \beta_i X_{t-i} + \sum_{i=1}^{p} \theta_i \varepsilon_{t-i}; \qquad (1.2)$$

where: x_{t-1} – factual power (kW), x_t – predicted power (kW), $\varepsilon_t, \varepsilon_{t-1}$ error; $\theta_1, \ldots, \theta_q$ – mowing average parameter, μ – average of factual data (kW), β_i – regression parameter.

1.4. Summary of analysed models

On a global scale, wind power generation is influenced by topographical and wind conditions. On a regional scale, wind speed varies according to the geographical location depending on the sizes of land and sea, and the presence of mountains and plain areas.

Despite many improvements there are still many disadvantages of wind power prediction methods (Table 1.1) (Liang et al., 2016; Tascikaraoglu et al., 2014).

Table 1.1. A brief comparison of main methods utilized for forecasting wind speed and power in the literature (Tascikaraoglu et al., 2014)

Wind speed/power forecasting approach	Advantages	Disadvantages
NWP models	Applicable for longer prediction horizons	Weakness in handling smaller scale phenomena, not suitable for short forecast times, requires large computational resource and time
Time series models (AR, ARMA, ARIMA, f-ARIMA, etc.) ANN-based models	Easy to find tools, comparatively basic structure, capability of correcting local for predictions	Requires a great deal of historic records, difficult to model nonlinear problems and decide the best structure
ANN-based models	Gains knowledge from training data, no need to specify any mathematical model a priori, high data error tolerance, higher adaptability to online measurements	Requires a training procedure and a large number of training data
SVM-based models	High generalization performance	Depends on tuning the parameters appropriately, complex optimization process and longer training time

Wind speed/power forecasting approach	Advantages	Disadvantages
Fuzzy logic models	Suitable for systems which are difficult to model exactly, relatively less complex	High complexity and a long process time in the case of many rules
Bayesian networks	Ability to handle missing observations and to avoid the over fitting of data, suitable for small training data sets, suitable for various input data	Requires relatively more effort, depends on the user's expertise level

Wind power forecasting methods and wind power forecasts still suffer from relatively high errors, depending on several factors, such as forecasting horizon, type of forecasting model, size of wind farm and geographic location. Also research (Kitous et al., 2012; Möhrlen et al., 2006) has shown that wind power prediction errors depend on seasonal and diurnal wind variations, local topographical and wind conditions. Due to this reason it is very important to analyse forecast errors and their dependence on wind speed, local topographical conditions and wind characteristics.

2. METHODOLOGY AND OBJECT

2.1. Object and characteristics

The object of the doctoral dissertation are wind power prediction methods, power forecasting errors and factors influencing the prediction accuracy. The object in four different wind farms in Lithuania was analysed. These farms are situated in Western part of Lithuania. Western part of Lithuania is located on the coastline of the Baltic Sea (Fig. 2.1.).

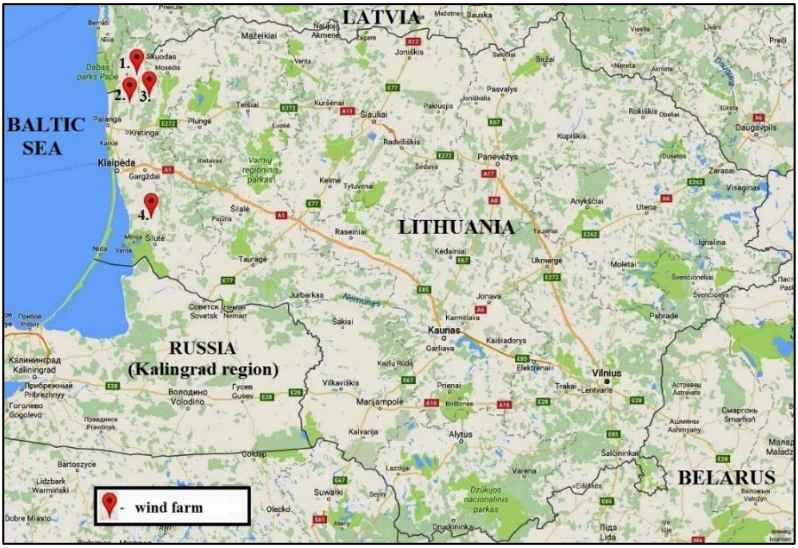

Fig. 2.1. Wind farms where power prediction errors were analysed (1-Sudenai WF, 2-Benaiciai WF, 3-Laukzeme WF, 4 - Ciuteliai WF)

Presented wind farms consist of turbines with different parameters, where hub height varies between 78-108 m, power capacity of turbines varies between 2-2.75 MW and rotor diameters between 82-108 m. Considering the fact that different numbers of turbines are placed in wind farms, total installed wind power of wind farms was completely different with capacity between 14-39.1 MW (Table 2.1).

Table 2.1. Parameters of wind farms where power prediction errors were analysed

Name of WF	**Installed power of WF (MW)**	**Number of wind turbines**	**Model of WT**	**Installed power of wind turbine (MW)**	**Hub height (m)**
Benaiciai WF	34	17	Enercon E82	2	98
Ciuteliai WF	39.1	17	Enercon E82	2.3	108
Laukzeme WF	16.5	6	Vestas V100	2.75	100
Sudenai WF	14	7	Enercon E82	2	78

2.2. Hybrid wind power prediction model

Designed wind power prediction method covers two main power prediction periods – long term for the planning of wind turbines and wind resource estimation; the second one – midterm (48h) – for wind power generation forecasting. The second one consists of two approaches – physical and statistical. The physical wind power prediction starts with the wind speed and wind direction data from numerical weather prediction (NWP) system. Wind speed and wind direction forecasted to 50, 80, 100 and 150 m height. In this case, a source of data, NWP system - High resolution local area model (HIRLAM) - was used. For the evaluation of local topographical conditions Wind atlas analysis and application software 9 (WAsP) were used. Both programmes cover the resolution of 5x5 km squares, and describe topographical conditions in squares. Statistical approach was used for the wind power correction and it covers the 3 last steps (Fig. 2.2).

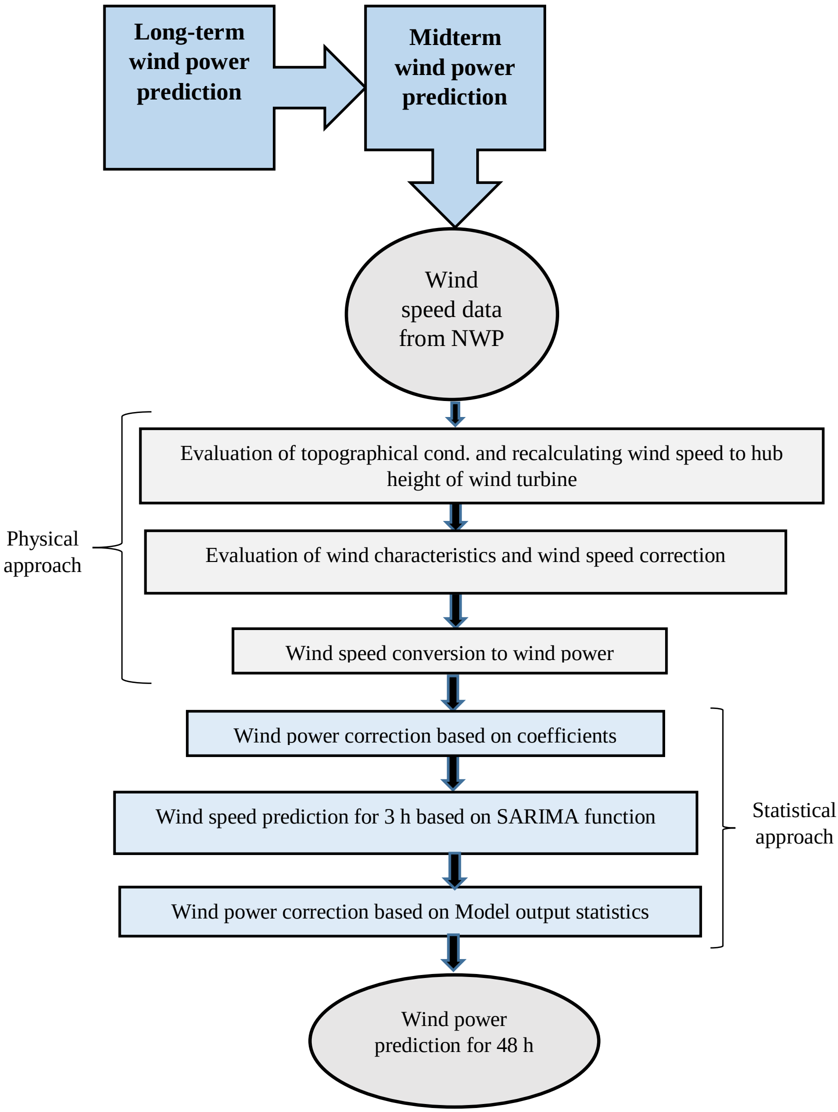

Fig. 2.2. Scheme of hybrid wind power prediction method

2.3. Data analysis methods

Weibull distribution is used for long-term wind speed and power estimation. Mathematically, Weibull probability density distribution function used to describe wind speed distribution has three parameters (Wais, 2017):

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} exp\left[-\left(\frac{v}{c}\right)^{k}\right]; \tag{2.1}$$

where: c – scale parameter; k – shape parameter; v – wind speed (m/s).

$$k = \left(\frac{\sum_{i=1}^{n} v_i^k ln(v_i)}{\sum_{i=1}^{n} v_i^k} - \frac{\sum_{i=1}^{n} ln\,(v_i)}{n}\right)^{-1}; \tag{2.2}$$

$$c = \left(\frac{1}{n}\sum_{i=1}^{n} v_i^k\right)^{\frac{1}{k}}; \tag{2.3}$$

where: v_i –wind speed (m/s); $k=2$.

For the evaluation of wind speed variation on different height, two formulae are used (Landberg, 2001). Logarithmic:

$$u_{VE} = u_{HIRLAM}\frac{ln\frac{z_{VE}}{z_0}}{ln\frac{z_{HIRLAM}}{z_0}}; \tag{2.4}$$

and exponential:

$$u_{VE} = u_{HIRLAM}\left(\frac{z_{VE}}{z_{HIRLAM}}\right)^{\alpha}; \tag{2.5}$$

where: u_{HIRLAM} – predicted wind speed (m/s); z_{VE} – hub height of wind turbine (m); z_{HIRLAM} – height where wind speed is predicted (m); α– roughness length (m).

Wind shear coefficient is estimated according to the following equation (Alessandrini et al., 2015):

$$\alpha = \frac{ln(V_2/V_1)}{ln\,(h_2/h_1)}; \tag{2.6}$$

where: V_2 and V_1 – wind speed (m/s) in higher and lower layers; h_2 and h_1 – height of higher and lower layers (m).

Turbulence intensity was evaluated according the following equation (Alessandrini et al., 2015):

$$TI = \frac{\delta_u}{\overline{v}}; \tag{2.7}$$

where: δ_u- standard deviation of wind speed (m/s); $\overline{v}$ – average wind speed (m/s).

Polynomial regression function in the analysed case is expressed as follows (Bolinger et al., 2012):

$$p(v) = a_0 + a_1 v + a_2 v^2 + \ldots + a_n v^n; \qquad (2.8)$$

where: p - estimated power (kW); v - wind speed (m/s), n - order of the polynomial; a_i -parameters of the polynomial function to be estimated (A_i, R, $i = 0, 1, \ldots, n$).

Sixth order polynomial function was analysed in the paper. The expressions of other parametric functions used for power output estimation of wind turbine are the following (Lydia et al., 2015)

$$p(v) = p_{\max}\left(1 - \mathrm{e}^{-\left(\frac{v}{\beta}\right)^{\alpha}}\right), \qquad \alpha, \beta > 0; \qquad (2.9)$$

$$p(v) = p_{\max}\left(1 + \left(\frac{\beta}{v}\right)^{\alpha}\right)^{-k}, \qquad \alpha, \beta, k > 0; \qquad (2.10)$$

where: p_{max} - maximum power output of wind turbine (kW); e - exponential function, a, b, k - parameters of the parametric functions to be estimated.

The analysed modified hyperbolic tangent function is given by:

$$p(v) = \frac{a_1 \mathrm{e}^{a_2 v} - a_3 \mathrm{e}^{-a_4 v}}{a_5 \mathrm{e}^{a_6 v} + a_7 \mathrm{e}^{-a_8 v}} + a_9; \qquad (2.11)$$

where: a_i - parameters of MHTan function to be estimated (i - 1, 2, …, 9).

ARIMA function is presented as follows (Hu et al., 2013):

$$y_t = \alpha + \phi_i Y_{t-1} + \ldots + \phi_p Y_{t-p} + \ldots + \theta_i \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t; \qquad (2.12)$$

where: α – constant term; ϕ_i – i-th autoregressive; θ_j – j-th moving average parameter; ε_t –error term at the time t; y_t – value of wind power (m/s, kW) at time t.

Model output statistics (MOS) method for predicted power correction is described according to the following equation:

$$P_{MOS} = a * P + b; \qquad (2.13)$$

where: P – predicted power (kW); a and b – statistical parameters.

In order to evaluate suitability of the analysed models, measure of normalized mean absolute percentage error (nMAPE) is calculated in the following formula (Hu et al., 2013):

$$n\,\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|p_i(P) - \hat{p}_i(P)\right|}{p(NP)} \cdot 100\%\,; \tag{2.14}$$

where: p_i - factual wind power (kW); $\hat{p}_i$ - predicted power (kW); $p(NP)$ - nominal wind turbine power (kW).

3. RESULTS AND DISCUSSION

3.1. Long term wind resources prediction

In order to determine accurate conversion process of wind power, Weibull distribution shape parameter *k*, and scale parameter *c*, four methods were used (Table 3.1). For a detailed analysis, data from meteorological stations in West Lithuania (Laukuva) was chosen (Fig. 3.1), where wind speeds are rather high (about 4 m/s at the height of 10 m above the ground level). Furthermore, measurement data collected in a continental part of the country location, in Varena meteorological station, was used (Fig. 3.2).

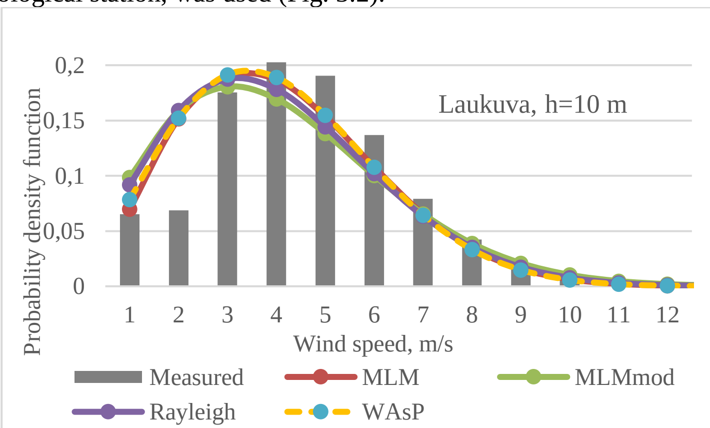

Fig. 3.1. Comparison of Weibull distributions based on different methods for estimating the distribution parameters for measured of wind speed data at 10 m height above the ground level in Laukuva meteorology station

The obtained research data presented in Table 3.1 shows that most of the methods are able to quite accurately determine Weibull parameters.

Table 3.1. Estimated Weibull distribution parameters based on various methods and measured wind speed data as Vi>0 in meteorological station of Laukuva in 2014 yearly period

Method	**k**	***c*, m/s**	**P, W/m²**	**R^2**	**RMSE, m/s**	**X^2**	**MAPE, %**
MLM	2,122	4,623	77,48	0,874	0,0221	0,00072	2,12
MLM_{mod}	1,926	4,6	83,21	0,812	0,027	0,00104	9,68
Rayleigh	2	4,574	77,67	0,829	0,0257	0,00095	2,3
WAsP	2,14	4,6	77	0,893	0,0224	0,0005	1,49

P_{eksper} = 75,87 W/m² *(Estimated experimentally)*

However, the WAsP method showed the best fit, and on the contrary, the largest relative errors were given by only the modified maximum likelihood method MLM_{mod}.

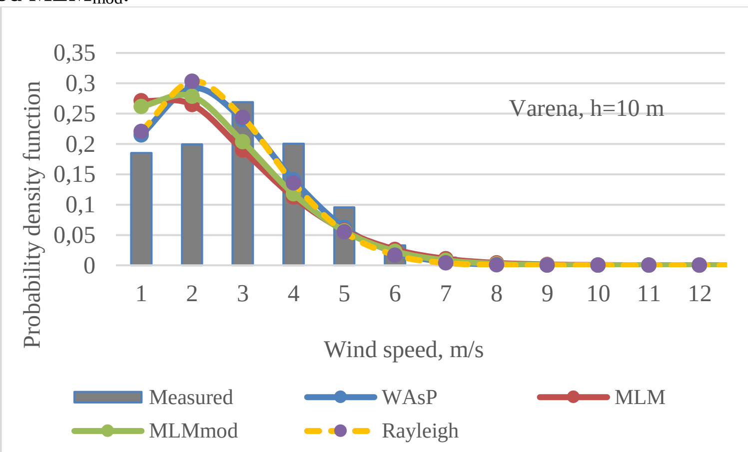

Fig. 3.2. Comparison of Weibull distributions based on different methods for estimating the distribution parameters for measured wind speed data at 10 m height above the ground level in Varena meteorology station.

In the case of small mean wind speeds, better description of wind power density distribution is received when Weibull parameters are calculated based on Rayleigh method (Table 3.2). There is another wind flow regime because the wind speed has more very low or zeros values.

Table 3.2. Estimated Weibull distribution parameters based on various methods and measured wind speed data as Vi>0 in meteorological station of Varena in 2014 yearly period

Method	k	*c*, m/s	P, W/m^2	R^2	RMSE, m/s	X^2	MAPE, %
MLM	1,575	2,67	21,29	0,815	0,0368	0,00135	12,60
MLM_{mod}	1,689	2,70	19,70	0,831	0,0352	0,00124	4,23
Rayleigh	2,000	2,83	18,45	0,872	0,0305	0,00940	2,38
WAsP	1,96	2,9	20,00	0,897	0,0275	0,00076	5,82

P_{eksper} = 18,90 W/m^2 *(Estimated experimentally)*

More accurate methods for identification of Weibull distribution parameters were sought for. This allowed finding a method that enables one to accurately determine wind speed profiles, describe and assess wind energy resources in the location. Statistically summarizing wind speed distribution data, Weibull two-parameter probability density function enables to clearly indicate wind resources for long term wind energy planning.

3.2. The influence of topographic conditions on power prediction accuracy

Wind farms in open areas by the coastline or higher relief sites usually are located where a very flat site surface prevails. However, in many cases, it is important to analyse and model local area surface roughness length in different directions. The investigation of roughness length modelling in Sudenai and Laukzeme farms was carried out. In Fig. 3.3 the comparison of combined and "different by wind directions" roughness lengths are presented. It was noticed that in case of usage of different roughness length depending on wind directions, wind power prediction nMAPE was insignificantly lower. Considering North and West direction in Laukzeme wind farm, power forecasting results were better, when combined surface roughness length for modelling was used. However, in total, better power prediction results were indicated in cases when roughness lengths indicators considering wind direction were chosen. It can be seen that the differences of power prediction errors were just up to 0.1%.

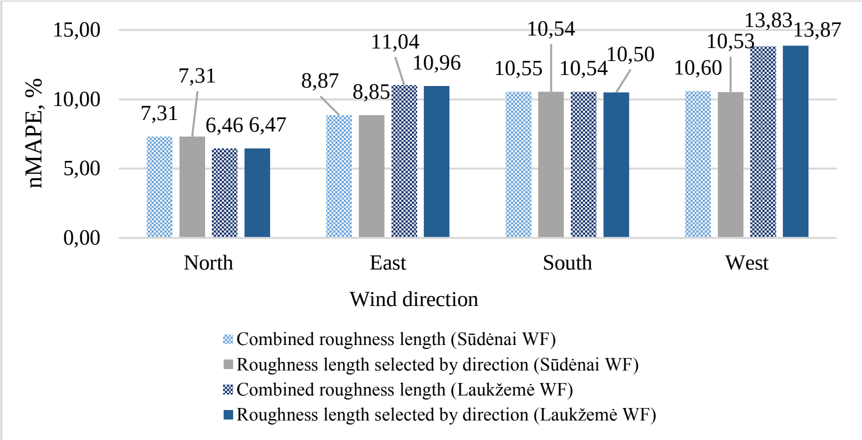

Fig. 3.3. Comparison of wind power prediction errors modelling combined and selected by direction roughness coefficients

As it was mentioned before, wind farms, where power prediction process and errors are analysed, are located on the coastline of the Baltic Sea. There is scarcer vegetation influenced by poorer soil. In order to analyse the influence of scarcer vegetation for power prediction accuracy, different forest roughness length was chosen: typical – 0.4, lower than typical – 0.2 and higher than typical – 0.5. The analysis of power prediction errors with different forest roughness lengths in Sudenai wind farm is presented in Fig. 3.4.

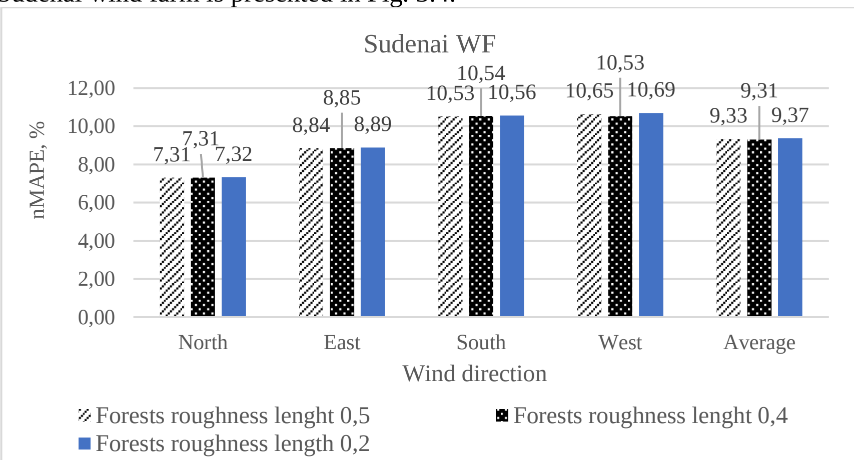

Fig. 3.4. Comparison of wind power prediction errors modelling surface roughness based on different trees coefficients in Sudenai wind farm

The lowest power prediction errors were in East and South direction, when 0.2 value was used. To compare, North direction results were best with modelling coef. 0.2 and 0.4, and West direction results were significantly better with coef. 0.4. The average wind power prediction errors present that in total the best suitable forest roughness modelling coef. is 0.4.

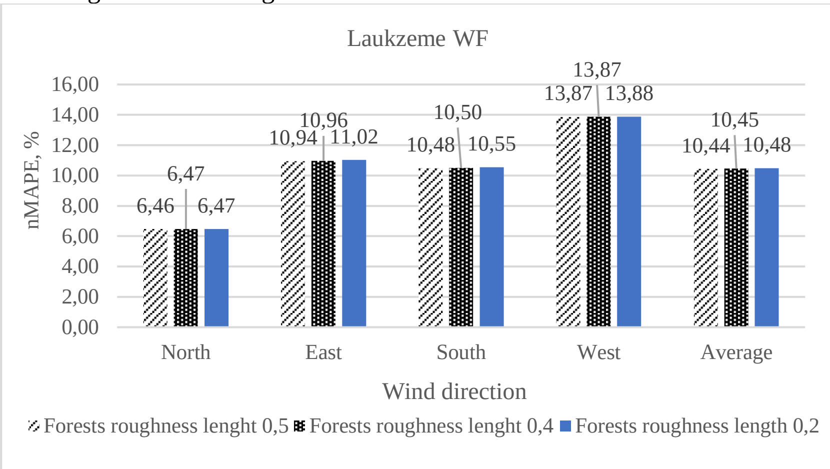

Fig. 3.5. Comparison of wind power prediction errors modelling surface roughness based on different tree roughness coefficients in Laukzeme wind farm

The same investigation in Laukzeme wind farm was carried out. Better results were identified in North, East and South directions with 0.2 modelling value and in West direction result, where the same results were with modelling 0.2 and 0.4 roughness lengths were identified. To compare the average of power prediction errors of all directions, 10.44% and 10.45% were with forests modelling lengths, 0.2 and 0.4 respectively.

The investigation of the influence of topographical variations on wind changes and wind power prediction accuracy was made and presented in Table 3.3.

Table 3.3. Wind power prediction errors including and not including the influence of topography

Tittle of wind farm	Wind power prediction error, %				Total error reduction, %
	Direct wind speed conversion (wind speed from NWP)	Corrected wind speed by surface roughness length	Corrected wind speed by percentage wind speed changes	Corrected wind speed by terrain changes	
Laukzeme WF	12.25	10.45	10.26	10.2	2.05
Sudenai WF	11.01	9.31	9.28	9.16	1.85

To conclude this chapter, it is very important to comment on the table above. It can be seen that direct wind conversion to power, from numerical weather prediction systems generated 11-12.3% prediction errors. Including wind speed correction coefficients, considering the surface roughness and terrain modelling, decreased the forecasting errors down to 2%.

3.3. The influence of wind conditions on the accuracy of power prediction

Different wind conditions influence the wind power generation and wind power forecasting errors. Wind power prediction errors and turbulence intensity are presented in Table 3.4. It was noted that during mixed wind speed conditions, turbulence intensity was the highest – 44% with power prediction nMAPE of 19.91%. To compare, during low wind speed conditions wind speed turbulence intensity reached 41% with prediction nMAPE of 11.47%. In terms of high wind conditions, turbulence intensity was 37.7% and wind power forecasting MAPE was 17.07%. These results revealed that there is no dependence on wind conditions and wind power forecasting error.

Table 3.4. Estimated turbulence intensity and power prediction error in different wind farms

<table>
<tr><th rowspan="3">Name of Wind Farms</th><th colspan="4">Turbulence intensity, %</th><th rowspan="3">Average, %</th><th rowspan="3">Prediction error, %</th></tr>
<tr><th>50 m</th><th>80 m</th><th>100 m</th><th>150 m</th></tr>
<tr><td colspan="4">Low speed wind conditions</td></tr>
<tr><td>Benaiciai WF</td><td>44.63</td><td>39.35</td><td>36.75</td><td>33.06</td><td rowspan="4">40.95</td><td rowspan="4">11.47</td></tr>
<tr><td>Ciuteliai WF</td><td>47.29</td><td>43.00</td><td>40.48</td><td>36.81</td></tr>
<tr><td>Laukzeme WF</td><td>47.71</td><td>43.09</td><td>41.03</td><td>38.03</td></tr>
<tr><td>Sudenai WF</td><td>47.81</td><td>41.82</td><td>39.12</td><td>35.30</td></tr>
<tr><td colspan="7">Mixed wind conditions</td></tr>
<tr><td>Benaiciai WF</td><td>45.94</td><td>43.18</td><td>42.04</td><td>41.48</td><td rowspan="4">44.01</td><td rowspan="4">19.91</td></tr>
<tr><td>Ciuteliai WF</td><td>42.11</td><td>40.34</td><td>40.02</td><td>40.91</td></tr>
<tr><td>Laukzeme WF</td><td>45.60</td><td>43.04</td><td>41.97</td><td>41.59</td></tr>
<tr><td>Sudenai WF</td><td>51.33</td><td>48.91</td><td>49.65</td><td>45.98</td></tr>
<tr><td colspan="7">High wind conditions</td></tr>
<tr><td>Benaiciai WF</td><td>34.56</td><td>37.28</td><td>36.18</td><td>34.56</td><td rowspan="4">37.68</td><td rowspan="4">17.07</td></tr>
<tr><td>Ciuteliai WF</td><td>43.06</td><td>41.44</td><td>40.57</td><td>38.92</td></tr>
<tr><td>Laukzeme WF</td><td>38.13</td><td>36.33</td><td>35.30</td><td>33.83</td></tr>
<tr><td>Sudenai WF</td><td>40.57</td><td>38.67</td><td>37.60</td><td>35.86</td></tr>
</table>

3.4. Wind turbines power curves modelling

Wind speed conversion to wind power is a key pillar of any wind power prediction model. It can be achieved by different techniques. In Fig. 3.6 four parametric functions are presented (M_1 - M_4).

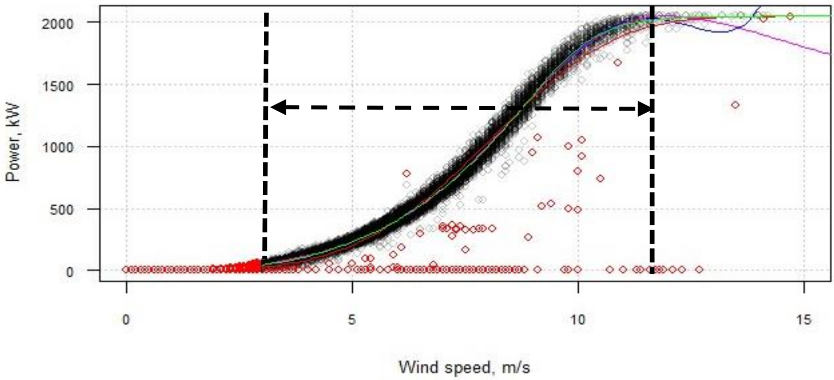

Fig. 3.6. Power curve approximations of different models *(M_1 –* blue*, M_2 – red, M_3 – green, M_4 – purple)*

Investigation of approximated power curve models M_1-M_4 are presented in Table 3.5. The results demonstrate that M_3 has the best fit to the initial data set, comparing to the other analysed models: M_3 gives the lowest value of MAPE of the analysed models (Table 3.5) and corresponds to the physical behaviour of generated power. In the analysed case, the models having more parameters do not allow to achieve more accurate results, giving lower value of MAPE.

Table 3.5. MAPE of estimated models

Model indicator	**Estimated power curve model**	**MAPE, %**
M_1	$p(v) = 3052.2 - 3286.6v + 1402.9v^2 - 301.7v^3 + 34.9v^4 - 2.02v^5 + 0.045v^6$	8.17
M_2	$p(v) = 2050\left(1 - \exp\left(-\left(\frac{v}{8.72}\right)^{4.04}\right)\right)$	13.86
M_3	$p(v) = 2050\left(1 + \left(\frac{10.06}{v}\right)^{17.06}\right)^{-0.183}$	8.11
M_4	$p(v) = \frac{-0.938e^{-28.041v} + 14.049e^{28.359v}}{-0.347e^{-28.728v} - 0.0003e^{28.006v}} - 97.091$	8.18

On the contrary, the worst results have shown model M_2 and this model is not acceptable for power curve approximation (MAPE 13.86%). To compare model M_1 and M_4 results are sufficient with MAPE 8.17% and 8.18%, respectively.

3.5. Statistical methods

Hybrid wind power prediction model involves statistical methods and functions in order to improve forecasting accuracy. As it was mentioned before, there are many statistical methods for power prediction, but one of the most popular ones is auto regression with integrated moving average (ARIMA). However, ARIMA method is not widely used for power generation, therefore it was adopted to seasonal variations method and calls (S)ARIMA. The comparison of these two methods is presented in Fig. 3.7.

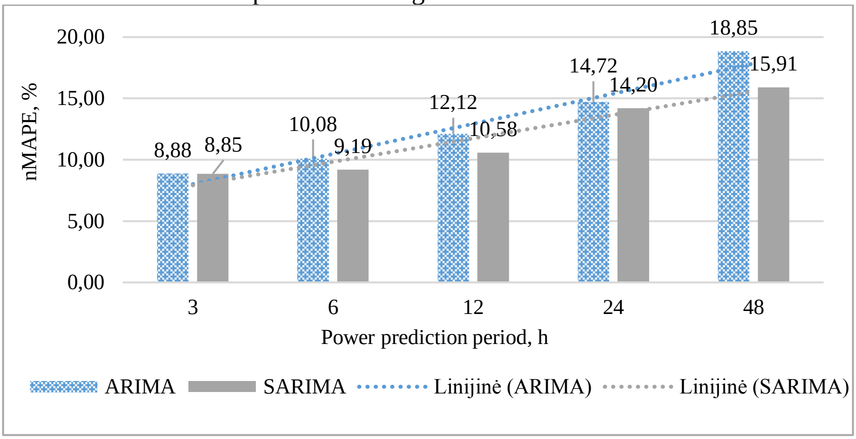

Fig. 3.7. Comparison of the accuracy of ARIMA and SARIMA models

It was noted that SARIMA model is more suitable for power generation with lower power forecasting error. For the first 3 h, wind power prediction error was 8.85% and the differences between these methods were not significant. However, for a longer period, the SARIMA model presented significantly better results. Due to this reason, SARIMA was used for statistical power prediction.

Wind power forecasting process, based on statistical methods, is very sensitive regarding the wind power volatility and wind periods. Power prediction errors based on SARIMA method during different wind conditions are presented in Table 3.6.

Table 3.6. Wind power prediction error distribution during different wind conditions periods

Wind power prediction period, h	Wind speed period (Low – L, High – H)				Average
	L-L	L-H	H-L	H-H	
3	4.20	10.44	9.78	8.78	8.30
6	3.68	11.33	12.53	14.70	10.56
12	4.04	16.32	17.57	24.32	15.56
24	5.45	26.02	16.57	30.06	19.52
48	5.26	36.46	18.29	35.89	23.98
Average	**4.53**	**20.12**	**14.95**	**22.75**	-

It was noticed that during all kinds of wind periods, the increment of wind power prediction errors is directly related to time horizon, when during the 3-48 h ahead period nMAPE increased from 8.3% to 23.98%. To evaluate a short-term time horizon, lowest errors were recognised during low wind speed period with 3.68% and the highest during high wind period with 14.70%.

Statistical wind power correction

In order to improve the power prediction accuracy statistical coefficients were estimated and integrated. Three groups of coefficients were estimated and chosen, and are presented in Table 3.7.

Table 3.7. Wind power forecasting including and not including correction coefficients

Period	Correction not included	Correction coef. when P<10 000 kW - 0.85 and when P>10 000 kW - 1.05	Correction coef. when P<10 000 kW 0.75 and when P>10 000 kW - 1.15	Correction coef. when P<10 000 kW - 0.65 and when P>10 000 kW - 1.35	Total decreased prediction error
1	7.04	6.30	8.12	8.73	0.74
2	8.72	8.65	9.33	9.96	0.07
3	3.52	3.54	5.46	5.50	-0.01
4	2.26	2.33	4.42	4.71	-0.06
5	7.96	7.84	9.87	9.64	0.12
Average	**5.90**	**5.73**	**7.44**	**7.71**	**0.17**

Investigation of acceptance of different coefficients indicates that 0.75 when P<10 000 kW and 1.15 when P>10 000 kW; 0.65 when P<10 000 kW – and 1.35 when P>10 000 kW power prediction errors were 7.44% and 7.71%, respectively. Meanwhile, prediction error not including coefficients were 5.9% and it means that the above-mentioned coefficients did not improve accuracy. However, including correction coef. 0.85 when P<10 000 kW and 1.05 when P>10 000 kW prediction error was the lowest – 5.73%.

Another statistical method for power prediction improvement calls Model output statistics. The method is based on linear relation between predicted and factual power during the period. The example of 36-days period to determine the relation is presented in Fig. 3.8.

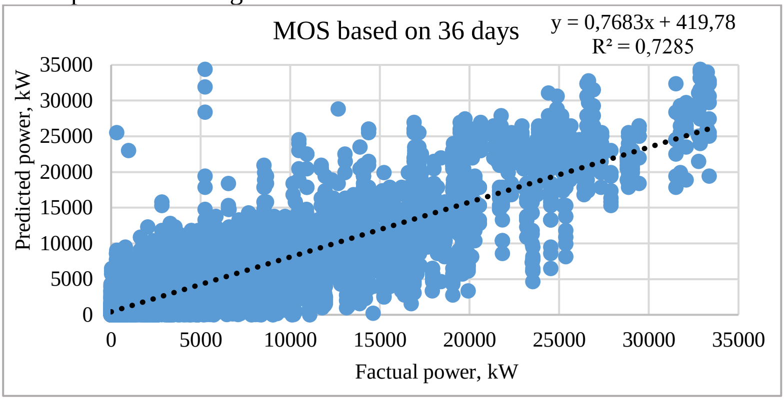

Fig. 3.8. Relation between predicted and factual power for 36-day period

In order to maximise the forecasting accuracy, it is necessary to determine what is the best suitable duration for identification of statistical method parameters. The results of this investigation are presented in Table 3.8 and they revealed that the best suitable duration is 6-12 days, comparing to 24-36 days. Besides, it was estimated also for periods of 1-3 days and more than 36-day results, but determination coefficient was less than 40%. It means that the relation between predicted and factual power was weak. To compare, in the period of 6-36 days the determination coefficient was in the limits of 0.65-0.75.

Considering the included and not included MOS method (6 days' adoption period) in Laukzeme and Sudenai wind farms, power prediction errors, not including MOS, were 10.15% and 9.24%, including MOS 9.30% and 9.22%, respectively. Meanwhile, during 12 days' adoption period, in Benaiciai and Ciuteliai wind farms errors, not including MOS, were 10.70% and 11.35%; including MOS 6.20% and 10.25%, respectively.

Table 3.8. Comparisons of wind power prediction errors including and not including MOS

Number of days for MOS estimation	Function	R^2	nMAPE, %
Benaiciai WF			
6	y = 0.8144x + 711.82	0.72	11.69
12	y = 0.7833x + 457.09	0.75	6.20
24	y = 0.7961x + 359.74	0.74	7.03
36	y = 0.7683x + 419.78	0.73	14.58
MOS not included	-	-	10.70
Ciuteliai WF			
6	y = 0.6676x + 1322.5	0.73	14.98
12	y = 0.6509x + 580.06	0.70	10.25
24	y = 0.7295x + 416.18	0.68	14.72
36	y = 0.7208x + 571.73	0.67	14.71
MOS not included	-	-	11.35
Laukzeme WF			
6	y = 0.8755x + 324.31	0.65	9.30
12	y = 0.8323x + 312.89	0.73	12.33
24	y = 0.8168x + 355.04	0.70	9.38
36	y = 0.7917x + 325.48	0.70	9.49
MOS not included	-	-	10.15
Sudenai WF			
6	y = 0.8616x + 8.8156	0.71	9.22
12	y = 0.8209x - 4.9589	0.75	10.81
24	y = 0.7622x + 30.711	0.69	11.56
36	y = 0.7258x + 5.7217	0.66	12.30
MOS not included	-	-	9.30

3.6. Summary of power prediction accuracy improvements

Detailed investigation of topographical conditions and wind characteristics was made, the statistical models for power curve approximation and wind power forecasting were identified. The results of power prediction accuracy improvements are presented in Table 3.9 and indicated up to 4.7% reduction in wind power prediction errors.

Table 3.9. Summary of methods when power prediction errors were decreased

Methods used for the reduction of power prediction errors	Decreased power prediction error, %
Evaluation of detailed topographical conditions	2.01
Integration of SARIMA function	0.86
The most suitable power curve method identification	0.1
Wind power correction methods	0.17
Wind power correction based on MOS function	1.6
Total decreased	4.7

It was evaluated that the main method for power prediction errors is the evaluation of topographical conditions, where power prediction error can be decreased by up to 2%. In terms of statistical methods, SARIMA method can improve power prediction accuracy by up to 0.9%, the best suitable power curve approximation function 0.1% and statistical predictable power correction methods by up to 1%.

CONCLUSIONS

The analysis of topographical and wind conditions in the wind farm sites, identification of the statistical methods for more accurate power prediction and the developed new hybrid model enable to draw the following conclusions:

1. During low wind speed conditions, the best suitable tool for wind speed distribution approximation is Rayleigh's method (MAPE 2.38%). To compare, during high wind speed conditions the best suitable method is WAsP with MAPE 1.49%.
2. Inclusion of different roughness length depending on wind direction in the wind power prediction process allows to reduce power forecasting errors. Detailed evaluation of topographical conditions improves wind power prediction accuracy by up to 2 percent.
3. It was estimated that during mixed wind conditions period, wind shear is the lowest (0.31) with the biggest wind power prediction error (19.91%). Meanwhile, lowest wind power prediction errors (11.47%) were identified during low wind speed period with wind shear coefficient of 0.35. During high wind speed period, power prediction error was 17.07% with shear coefficient of 0.4. The results identified there is no linear dependence between wind power prediction errors and wind shear.
4. It has been determined that the most suitable method for wind turbine power curve modelling is the parametric function (M_3) with error 8.11%.
5. The investigation of time series models revealed that the best statistical function for power prediction is SARIMA and it is acceptable for 3-hour forecasting with 8.3% error. Model output statistics method increases power prediction accuracy by up to 0.7%.
6. The developed hybrid method predicts wind turbine power by up to 4.7% more accurately, comparing to direct wind speed conversion from NWP data.

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REZIUMĖ

Darbo aktualumas

Didėjant vėjo elektrinių skaičiui Lietuvoje ir pasaulyje, sunkiai prognozuojamas ir nuolatos kintantis vėjo greitis sukelia elektros balansavimo ir rezervavimo problemų elektros energetikos sistemoje (EES). Pagrindinė to priežastis – nepakankamai tikslūs vėjo greičio ir vėjo elektrinių generuojamos galios prognozės modeliai bei metodai. Vėjo elektrinių galios prognozavimo procesas vadovaujasi vėjo greičio prognozavimu, konvertavimu į vėjo elektrinių galią bei statistiniu galios patikslinimu. Šiuose žingsniuose galimos prognozavimo paklaidos, todėl būtina ieškoti naujų tikslesnių metodų bei veiksnių, turinčių įtaką paklaidų susidarymui.

Vėjo elektrinių galios prognozavimas skirstomas į itin trumpalaikę (iki 6 valandų), trumpalaikę (iki 24 valandų), vidutinės trukmės (iki 48 valandų), ilgalaikę (iki 72 valandų) ir itin ilgalaikę (>72 valandų) prognozę. Kuo ilgesnis vėjo elektrinių galios prognozavimo laikotarpis, tuo didesnės prognozavimo paklaidos yra gaunamos. Šios prognozavimo paklaidos gali būti klasifikuojamos į fazines (angl. *phase error*) ir amplitudines (angl. *level error*). Fazinės paklaidos atsiranda dėl staigaus vėjo greičio kitimo laikotarpiu, kai nesutampa prognozuojamos ir faktinės generuojamos vėjo elektrinės galios fazės. Amplitudinės paklaidos atsiranda tada, kai prognozuojamos ir faktinės vėjo elektrinės galios fazės sutampa, tačiau prognozuojamos galios vertė yra mažesnė arba didesnė už faktinę vertę. Generuojamai galiai prognozuoti taikomi statistiniai ir fizikiniai metodai. Itin trumpalaikiam (iki 6 valandų) galios prognozavimo laikotarpiui tinkamiausi yra statistiniai metodai. Ilgesniam nei 6 valandų laikotarpiui daugeliu atvejų tinkamesni fizikiniai galios prognozės metodai. Tačiau pasitaiko atvejų, kai prognozuojant vėjo elektrinių galią vidutinės trukmės laikotarpiui, tinkamesni yra statistiniai prognozavimo metodai. Todėl labai svarbu tirti įvairių metodų tinkamumą bei nustatyti prognozavimo paklaidas lemiančius veiksnius.

Lietuvoje vėjo elektrinių galia prognozuojama 24 valandų laikotarpiui ir sudaromas energijos gamybos bei vartojimo planas. Tačiau, nesant pakankamai tikslios vėjo elektrinių galios prognozės, gaunamas netikslus energijos gamybos planas. Todėl valdant EES tinklą patiriama nuostolių, kurie atsiranda tada, kai perteklinė pagaminta vėjo elektrinėse energija yra parduodama už žemesnę nei vidutinė rinkos kainą. Tokiu atveju, kai vėjo elektrinės energijos pagamina mažiau nei planuota, reikalingi papildomi galios rezervai, kurie apskaičiuojami pagal vėjo elektrinių galios prognozavimo paklaidas. Tad siekiant užtikrinti patikimą EES darbą bei sumažinti sistemos galios balansavimo ir rezervavimo kaštus, svarbu kuo tiksliau prognozuoti vėjo elektrinių galią.

Ištyrus vėjo elektrinių galios prognozavimo paklaidų susidarymą lemiančius veiksnius bei integravus optimalius prognozavimo metodus į bendrą hibridinį prognozavimo metodą, būtų galima tiksliau prognozuoti vėjo elektrinių generuojamą galią, sumažinti galios rezervo palaikymo kaštus bei padidinti EES patikimumą, o tai palengvintų vėjo elektrinių integracijos plėtrą įgyvendinant Europos Sąjungos ir Lietuvos strateginius tikslus.

Pavadinimas

Vėjo elektrinių generuojamų galių prognozės tikslumą lemiančių veiksnių tyrimas

Darbo tikslas

Ištirti vėjo elektrinių generuojamos galios prognozės paklaidas lemiančius veiksnius ir sukurti kompleksiškai aplinkos sąlygas vertinančią bei tiksliau VE generuojamą galią leidžiančią prognozuoti metodiką.

Uždaviniai

1. Ištirti vėjo galios tankio pasiskirstymą įvertinančių metodų tikslumą, esant skirtingiems vėjo greičiams.
2. Išanalizuoti topografinių sąlygų ir vėjo charakteristikų įtaką vėjo elektrinių galios prognozavimo tikslumui.
3. Identifikuoti funkcijas, tiksliausiai aprašančias vėjo elektrinių galios kreives.
4. Nustatyti tiksliausiai vėjo elektrinių galią prognozuojančius statistinius metodus ir parinkti tinkamiausias statistines priemones prognozavimo paklaidoms mažinti.
5. Sukurti hibridinį galios prognozavimo metodą, leidžiantį tiksliau prognozuoti vėjo greitį ir vėjo elektrinių galią.

Išvados

Atlikta vietovių, kuriose yra vėjo elektrinės, topografinių ir vėjuotumo sąlygų analizė, nustatyti statistiniai metodai ir priemonės, skirtos tiksliau prognozuoti vėjo elektrinių galią, bei sukurtas hibridinis metodas leidžia daryti šias išvadas:

1. Ištyrus vėjo galios tankio pasiskirstymą įvertinančių metodų tikslumą nustatyta, jog esant mažam vėjo greičiui (< 4 m/s), tiksliausiai vėjo greičio pasiskirstymo funkcijos parametrus aprašo Reilėjaus metodas (aproksimavimo paklaida 2,38 %), o esant dideliam vėjo greičiui (> 4 m/s) – tinkamiausias WAsP metodas (aproksimavimo paklaida 1,49 %).
2. Atlikus vėjo elektrinių galios prognozės paklaidų tyrimus nustatyta, jog prognozuojant vėjo elektrinių galią tikslinga išsamiai vertinti topografines sąlygas, todėl, kad tai leistų vėjo elektrinių generuojamos galios prognozės tikslumą padidinti iki 2 %.
3. Ištyrus vėjo charakteristikų įtaką VE galios prognozės tikslumui nustatyta, kad nėra tiesinės priklausomybės tarp vėjuotumo charakteristikų ir vėjo elektrinių

generuojamos galios prognozės paklaidų, todėl, kad didžiausios prognozavimo paklaidos (19,91 %) nustatytos, esant mišrioms vėjuotumo sąlygoms, mažiausios paklaidos – mažo vėjuotumo laikotarpiu (11,47 %), o vėjuotu laikotarpiu prognozavimo paklaida siekė 17,07 %.

4. Ištyrus vėjo elektrinių galios kreives aprašančių funkcijų tikslumą nustatyta, jog tiksliausiai galios kreivę aprašo parametrinė funkcija, kurios sąlygojama aproksimavimo paklaida siekia 8,11 %.

5. Ištyrus tiksliausiai vėjo elektrinių galią prognozuojančius statistinius metodus nustatyta, kad tinkamiausias statistinis galios prognozavimo metodas yra SARIMA. Šis metodas tinka itin trumpo laikotarpio (iki 3 valandų) VE galios prognozei (paklaida 8,3 %). Taip pat įvertinta, jog taikant tiesinės regresijos patikslinimo metodą, prognozuojamos VE galios tikslumą galima padidinti iki 1,6 %.

6. Sukurtas naujas hibridinis kompleksiškai topografines ir meteorologines sąlygas įvertinantis metodas vėjo elektrinių generuojamą galią leidžia prognozuoti iki 4,7 % tiksliau nei tiesiogiai konvertuojant skaitmeninės orų prognozės (SOP) duomenis (vėjo greitį) į VE galią.

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