www.czasopisma.pan.pl PAN POLSKA AKADEMIA NAUK www.journals.pan.pl

BULLETIN OF THE POLISH ACADEMY OF SCIENCES
TECHNICAL SCIENCES, Vol. 67, No. 1, 2019
DOI: 10.24425/bpas.2019.127340

Assessment of wind energy resources using artificial neural networks – Case study at Łódź Hills

R. KORUPCZYŃSKI[1]* and J. TRAJER[2]

[1] Electrotechnical Institute, Pożaryskiego St. 28, 04-703 Warsaw, Poland
[2] Warsaw University of Life Sciences – SGGW, Faculty of Production Engineering, Nowoursynowska St. 164, 02-787 Warsaw, Poland

Abstract. The aim of this paper is to answer the question: Are the Łódź Hills useful for electrical energy production from wind energy or not? Due to access to short-term data related to wind measurements (the period of 2008 and 2009) from a local meteorological station, the measure – correlate – predict approach have been applied. Long-term (1979–2016) reference data were obtained from ECWMF ERA-40 Reanalysis. Artificial neural networks were used to calculate predicted wind speed. The obtained average wind speed and wind power density was 4.21 ms^{-1} and 70 Wm^{-1}, respectively, at 10 m above ground level (5.51 ms^{-1}, 170 Wm^{-1} at 50 m). From the point of view of Polish wind conditions, Łódź Hills may be considered useful for wind power engineering.

Key words: wind speed, artificial neural network, wind resource, measure-correlate-predict.

1. Introduction

Renewable sources of energy have been increasingly used over the recent years. Fossil fuels are running out, and some CO_2 emission limits are introduced, hence there is a strong need for looking for other energy sources worldwide, as well as in Poland [1]. One of free renewable resources of energy is wind. Wind energy might be converted by a wind turbine into electrical energy. The nominal power of a typical wind turbine is not very high, it is equal to about 2 to 3 MW [2]. Often, many wind turbines are concentrated in one place and form a wind farm. The total cost of a typical farm is quite high (i.e. 200 MW land-based, USA): 1690 kW of installed power [3]. However, there is no other option, since, according to the European Union Directive, renewable energy share in the total energy has to amount to 20% by 2020 [4].

Efficient use of wind energy requires choosing a site with the highest possible wind speeds, as temporary, electrical power of a turbine is proportional to the cube of wind speed [5]. But the wind speed is too variable parameter. It can be described mathematically by means of statistical methods [6]. The value of wind speed is determined at the given site by the method of real measurement. There is a potential risk of measurement campaign execution at a period with higher than usual wind speeds. Hence, the measurements data should be available in long-term period of time, i.e. 10 [7] or 20–25 years [8]. This kind of data is usually held by national meteorological services.

From the wind farm developer point of view, a waiting time of investment launching may not be too long. The measurements period should be as short as possible: the standard is one year [9]. But this is contradictory to what was stated above that the period should be at least 10 years.

A solution to the problem is the application of Measure – Correlate – Predict method (MCP) [10]. It requires two short-term data sets: one from meteorological station at given place, and the other one, so called reference dataset. The sets (here for the period of 2 years) are the basis of artificial neural network model training. After the training, the model is used to predict wind speed time series at a given place with the third, long-term reference dataset. The artificial neural network model is better than a mathematical function, because it better describes the correlation between the datasets being analysed, including many influencing factors. After positive verification of the model, wind energy resources at the given place can be evaluated considering the following parameters: mean wind speed, wind speed distribution and wind power at a given height, usually equal to the proposed wind turbine height.

The aim of this paper is to create the prediction model of wind resources at Łódź Hills. After the model application, wind energy resources will be determined, as well as usability of subject location for wind power engineering.

2. Location

Łódź Hills (Heights) are the southern part of the Mazovian Lowland. In the physico-geographical regionalization of Poland this Mezoregion has the number of 318.82 [11]. The landscape is made up of rolling upland. A few cities are located in this region, such as: Łódź (the largest), Zgierz, Brzeziny, Stryków and Rzgów. In the northern part of the region, Łódź Hills Landscape Park is located. Apart from the area of Łódź, where industrialised landscape dominates, the rest of the region has agricultural character. Hence, this terrain may be convenient for wind energy developments. As stated in [12], Łódź Hills are located

*e-mail: rkorupcz@poczta.onet.pl

Manuscript submitted 2018-03-27, revised 2018-09-17, initially accepted for publication 2018-09-21, published in February 2019.

on the border of the beneficial and the highly beneficial wind zones, according to the classification published by the Institute of Meteorology and Water Management. In the whole Łódź Province, there are wind farms, i.e. at the Kamieńsk Mountain, in the vicinity of the cities of Głuchów and Słupia.

3. Measurement station

The short-term data were obtained from the meteorological measuring station (Fig. 1), located at the Agricultural Experimental Farm (AEF) of Warsaw University of Life Sciences at Żelazna [13]. The station was at the height of 174 m above sea level (coordinates: 51.875286 N, 20.112762 E). Wind speed was measured by anemometers at two heights: 6 m and 12 m above ground level (a.g.l.). Accuracy of the anemometers was 2%. Originally, data were saved as one-minute averages. For the purpose of this paper, data were averaged by 6 hours, as the reanalysis data. In this paper, data for two years: 2007 and 2008 were used.

Fig. 1. Meteorological measuring station at Agriculture Experimental Farm (AEF) of Warsaw University of Life Sciences at Żelazna (2008)

4. Reanalysis

Meteorological reanalysis is the second analysis of meteorological measurements time series on the global [14] or regional scale [15]. Incorrect measurements are rejected, and the data from different sources are integrated. Mathematical model used for data description is constant, and it will remain the same in the future. Results of reanalysis are available at uniform grid of geographical coordinates [16]. In this paper data from ERA Interim Reanalysis were used [17]. The reanalysis was prepared by the European Centre for Medium Range Weather Forecasts (ECMWF). The time period of available data is quite long: 1979 to present (2016). In this paper, reanalysis plays a role of reference meteorological station for the MCP method.

5. Methodology

5.1. Measure – Correlate – Predict Method. The Measure – Correlate – Predict method was first described by Derrick [18]. In this method, the required dataset consists of two parts: one-year measurements data from the given site and multi-year data from a local meteorological station. Beside the wind speed, the wind direction can be used [19]. The period of time, in which the measurements were made at the given site, has to be included in the long-term dataset from the reference meteorological station. Next, the correlation function between the data from the reference station and the site is calculated, based on the common period of time in both datasets. The last step involves using the correlation function for the calculation of long-term prediction at the given site [20]. Long-term data from the reference station are used as input data.

The correlation can be determined using different methods, i.e.: linear regression [19–21], variance ratio [19], artificial neural network [22, 23], support vector machines [24]. A comprehensive and detailed review of many MCP variants is included in [25].

The accuracy of the MCP method depends on various factors and changes at various locations. Mean wind speed prediction error equal 3–10% have been reported [20, 26]. From the point of view of energy yield, error of approx. 4% has been mentioned in [27].

In this paper, the data correlation was determined by an artificial neural network. An advantage of the artificial neural network is finding of a relationship between independent variables and a dependent variable even if the relationship is highly nonlinear [28]. As is stated in [29], the artificial neural network approximates a dependence between variables much better than any theoretical method.

5.2. Neural prediction model. The first part of data, were input (explanatory) variables obtained from the reanalysis (Fig. 2):

- day of year, in which the measurement was taken – $d(1 \ldots 365)$,
- hour, in which the measurement was taken – $h\{0, 6, 12, 18\}$,
- wind speed at the reference station measured 10 metres above ground level – $v_{10}(\mathrm{ms}^{-1})$,

Fig. 2. A concept of artificial neural wind speed prediction model (Own elaboration)

- air temperature – $t(°C)$,
- atmospheric pressure – $p(hPa)$,
- wind direction – $s(°)$.

The second part of data used for the construction of the model are from a meteorological station. The measurements were taken for the period of two years, i.e. 2008 and 2009. Wind speed measured 12 metres above ground $v_{12}(ms^{-1})$ is the output variable, Fig. 2. According to the data obtained from the meteorological reanalysis, the results of measurements were averaged over 6 hours. 4 values were obtained for the following times of the day: 0:00, 6:00, 12:00 and 18:00.

In this research, there was a lack of easy access to long-term data from a real meteorological station, wchich was close to considered location. Hence, the data was taken from reanalysis.

Statistica package workspace (version 13) was used to analyse data and construct the prediction model. The input data were normalized. The proportions of training, test and validation data were: 70%, 15%, 15% rescpectively. Neural networks were tested for structure, the number of hidden neurons as well as the number of input variables were changed. The algorithms for artificial neural network training were: the BFGS (Broyden-Fletcher-Goldfarb-Shanno) and Scaled Conjugate Gradient algorithms [30]. Initial weights were chosen, based on the random methods using the normal and uniform distributions [30]. Sensitivity analysis was applied for that purpose. The best network was selected according to the following criteria: structure, values of correlation coefficients and mean squared error values (E_{SOS}) for the training, validation and test sets:

$$E_{SOS} = 1/n \sum_{n=1}^{n} \left(y^{i}_{real} - y^{i}_{model}\right)^2, \tag{1}$$

where: y_{real}, y_{model} – real results and results from the model, respectively, n – number of trials.

Alfred Rappaport [31] defines sensitivity analysis in mathematical terms as a test specifying “how potential changes and errors in the values of parameters influence the output of the model”, as opposed to other scientists. The application of analysis in artificial neural networks is viewed in a similar way. This technique enables the determination of the relative impact of input variables on the network efficiency, by multiple testing a given artificial neural network after removing certain variables (Typically, according to the applied method of missing data replacement, the mean value is fed at the input of the neuron corresponding to the variable in question). It was assumed that the measure of sensitivity analysis is the quotient of errors I_{SOS}, i.e. the quotient of the mean squared error $E_{SOS}(x_i)$, omitting the x_i variable by the means square error E_{SOS}, obtained for all variables, determined by means of the artificial neural network:

$$I_{SOS} = \frac{E_{SOS}(x_i)}{E_{SOS}}. \tag{2}$$

For each input the measurements were performed in ten evenly spread locations, with the minimum and maximum values being endpoints. During calculations, the values of the remaining input variables were set at medium level. For each dependent variable, a separate spreadsheet was created. The detailed method of calculations was presented in [32]. Separate sensitivity analyses for training, validation and test trials might be performed. Global sensitivity analysis returns cumulative results for all samples. In the Statistica software the sensitivity analysis runs almost automatically, without the assistance of user.

5.3. Wind energy resources. The artificial neural network wind prediction model (MCP) gives time series of wind speed values at a given height above ground level (here: 12 m, v_{12} at Fig. 2). Hence, it is necessary to convert the wind speed time series to other heights, i.e wind turbine heights. The conversion may be performed using the power law (Hellman formula) [33]:

$$v_h = v_{ref}\left(\frac{h}{h_{ref}}\right)^{\alpha}, \tag{3}$$

where: v_h, $v_{ref}(ms^{-1})$ are wind speeds at heights: h and h_{ref} respectively, α $(-)$ is the exponent. The latter can be determined, if the wind speeds v_{h1} and v_{h2} measured at two different heights h_1 and h_2 are known [33]:

$$\alpha = \frac{ln(v_{h2}) - ln(v_{h1})}{ln(h_2) - ln(h_1)}, \tag{4}$$

or, if the roughness lenght z_0 is known [5]:

$$\alpha = \frac{1}{ln\left(\frac{h_{ref}}{z_0}\right)}. \tag{5}$$

The roughness z_0 can be estimated, based on Davenport classification [34, 35]. In eq. 4 annual average wind speeds have to be used [36].

Wind speed may change rapidly, its value varies very much at day as well as over the year. This variability can be described only by statistical methods, e.g. the Weibull probability distribution [37, 38]:

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} e^{-(v/c)^k}, \tag{6}$$

where: $f(v)$ is the probability of wind speed v, k is shape parameter (without dimension), c is scale parameter (ms^{-1}). After the summation of eq. 6, cumulative Weibull distribution is: [39]:

$$F(v) = 1 - e^{-\left(\frac{v}{c}\right)^k}, \tag{7}$$

where: $F(v)$ is cumulative probability of wind speed. The k, c, parameters may be calculated by a linear regression method, after taking of natural logarithm from both sides of equation eq. 7 [39]:

$$ln\big(-ln\big(1 - F(v)\big)\big) = kln(v) - kln(c). \tag{8}$$

The regression equation then assumes the following form:

$$y = \beta_0 + \beta_1 x, \tag{9}$$

where:

$$y = ln\big(-ln\big(1 - F(v)\big)\big), \tag{10}$$

$$\beta_0 = -kln(c), \tag{11}$$

$$\beta_1 = k, \tag{12}$$

$$x = ln(v). \tag{13}$$

The calculated coefficients, k and c, clearly characterize wind speed distribution at the given location.

Another parameter of wind resources is wind power density. It can be calculated using average wind speed $v_{ave}\left(\text{ms}^{-1}\right)$ as $p_{ave}\left(\text{Wm}^{-2}\right)$ [40]:

$$p_{ave} = \frac{1}{2}\rho v_{ave}^3, \tag{14}$$

where: ρ is air density: 1.225 kgm^{-3} at sea level and at 15°C. Average wind speed v_{ave} is calculated from wind speed time series. The typical averaging period is one year. If the Weibull coefficients are available, wind power density p_w can be calculated by [40]:

$$p_w = \frac{1}{2}\rho c^3 \Gamma\left(\frac{k+3}{k}\right). \tag{15}$$

All the calculations, however, do not answer the question about the values of wind parameters sufficient for a given location to be considered useful from the point of view of electrical energy production. In the USA, National Renewable Energy Laboratory recommends [41, 42] at least $p_{ave} = 300$ Wm^{-2} at 50 m a. g. l. or $p_{ave} = 150$ Wm^{-2} at 10 m a. g. l. It corresponds (Eq. 14) to the average wind speeds v_{ave} equal 6.4 ms^{-1} and 5.1 ms^{-1}, respectively. In the UK, a two-year study of 57 locations carried out by The Energy Saving Trust showed that v_{ave} has to be at least 5 ms^{-1} or [43]. The report published by the European Environment Agency [44] contains the results of the calculation of wind energy generation costs across Europe. Onshore wind locations with speed classes lower than 4.0 ms^{-1} were excluded from the analysis, due to unprofitability. Often, local administrative and economic conditions may have impact on economic viability of wind energy project. In Polish conditions one can accept that one-year average wind speed should be higher than 4.0 ms^{-1} [45, 46]. Average wind speeds over 6 ms^{-1} do not occur in Poland [46].

6. Results

6.1. Verification of the prediction model. The network with the best parameters (the greatest values of correlation coefficient for the validation and test set, and as close to each other as possible, with the least complex artificial neural network structure) was selected out of 20 networks, following a series of tests. The parameters of the selected multilayer perceptron MLP 6:7:1 are presented in Table 1.

Table 1
Multilayer perceptron model of the wind speed MLP 6:7:1

Correlation coefficient (learning)	Correlation coefficient (testing)	Correlation coefficient (validation)	Error (learning)	Error (testing)
0.912	0.903	0.919	0.364	0.388

Error (validation)	Learning algorithm	Error function	Activation function (hidden)	Activation function (output)
0.358	BFGS 121	SOS	Tanh	Linear

Sensitivity analysis for this model indicates that the most significant input variables are, Table 2: wind speed at 10 metres above ground level in the reference station v_{10} (the most significant), day of year d, temperature t, pressure p in the analysed day. The direction of wind s and the time of the 24-hour day h are of lesser statistical significance.

Table 2
Global sensitivity analysis of the model MLP 6:7:1

$v_{10}[\text{ms}^{-1}]$	d	t[°C]	p[hPa]	s[°]	h
5.563	1.299	1.115	1.054	1.027	1.009

An attempt to simplify the model by reducing the number of input variables to 4. As previously, 20 artificial neural networks were tested, and the best network was selected according the same criterion. The best model was multi-layer perceptron MLP 4:8:1 Fig. 3, whose parameters are presented in Table 3.

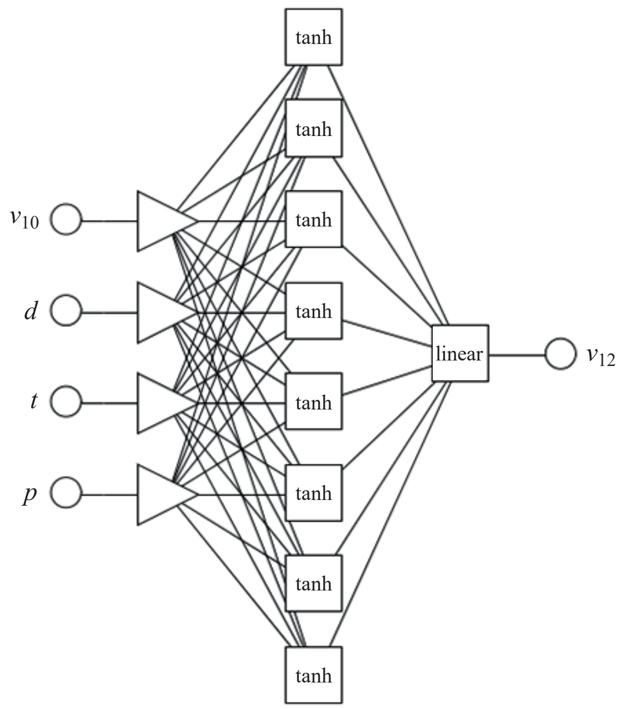

Fig. 3. Structure of the artificial neural network MLP 4:8:1 (Own elaboration)

The correlation coefficients presented in Tables: 1 and 3 were statistically significant at an level of 0.05.

Table 3
Multilayer perceptron model of the wind speed MLP 4:8:1

Correlation coefficient (learning)	Correlation coefficient (testing)	Correlation coefficient (validation)	Error (learning)	Error (testing)
0.908	0.901	0.916	0.380	0.394
Error (validation)	Learning algorithm	Error function	Activation function (hidden)	Activation function (output)
0.367	BFGS 75	SOS	Tanh	Linear

Sensitivity analysis of this model indicates that the rank of the same variables is similar, Table 4. The results, and the graphs of dependencies between the variables being analysed are almost identical, Fig. 4–6.

Table 4
Global sensitivity analysis of the model MLP 4:8:1

$v_{10}[\mathrm{ms}^{-1}]$	d	$t[°\mathrm{C}]$	$p[\mathrm{hPa}]$
5.500	1.175	1.151	1.027

The graph (Fig. 4 shows linear dependence between wind speed measured at the reference station v_{10} and wind speed in the selected point at 12 m – v_{12}, predicted by the artificial neural network model. The graph (Fig. 4) also shows that the correlation between these two speeds is smaller during the winter.

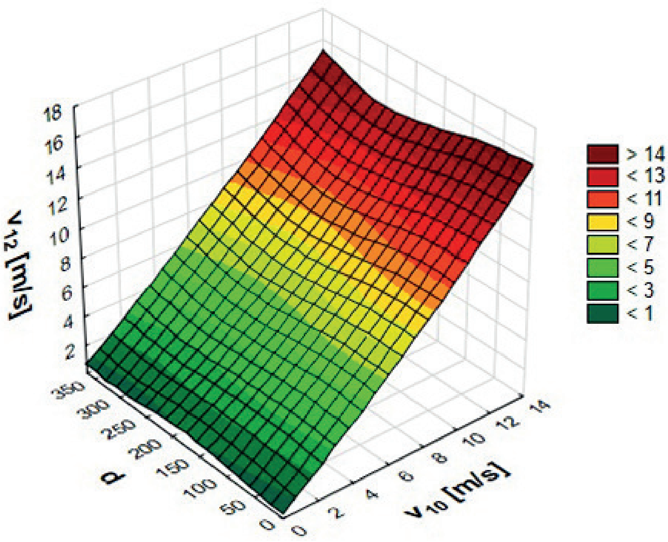

Fig. 4. Wind speed v_{12} from the prediction model versus the wind speed at the reference base station v_{10} and day of year d (Own elaboration in Statistica)

The presented graph (Fig. 5) shows that the speed values recorded at the measuring station increase together with the temperature, which confirms the observation about the character of changes during the winter, shown by the previous graph.

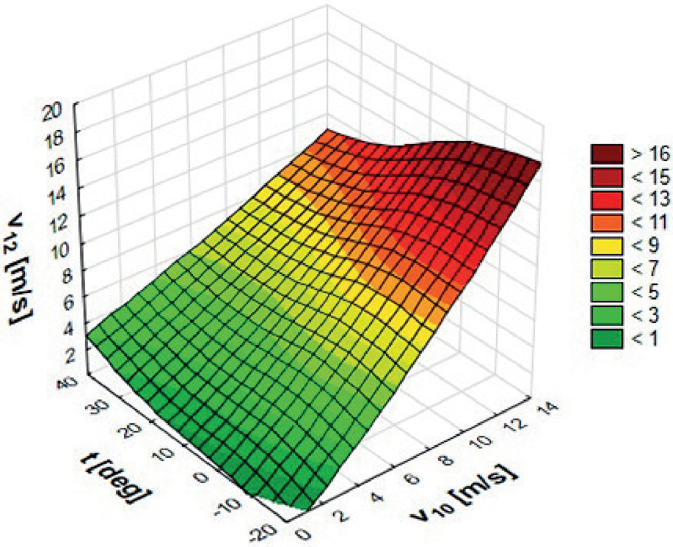

Fig. 5. Wind speed v_{12} from the prediction model versus the wind speed at the reference base station v_{10} and air temperature t (Own elaboration in Statistica)

The last graph (Fig. 6) indicates that higher atmospheric pressure has inversely proportional impact on the value of wind speed in the measuring point. Comparison of the results of wind speed from the model MPL 4:8:1 with the real data from the period 2008 – 2009 was shown in Fig. 7.

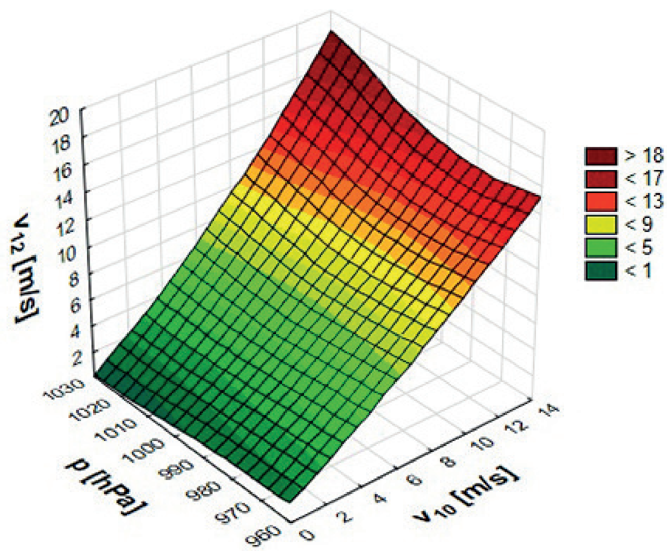

Fig. 6. Wind speed v_{12} from the prediction model versus the wind speed at reference base station v_{10} and air atmospheric pressure p (Own elaboration in Statistica)

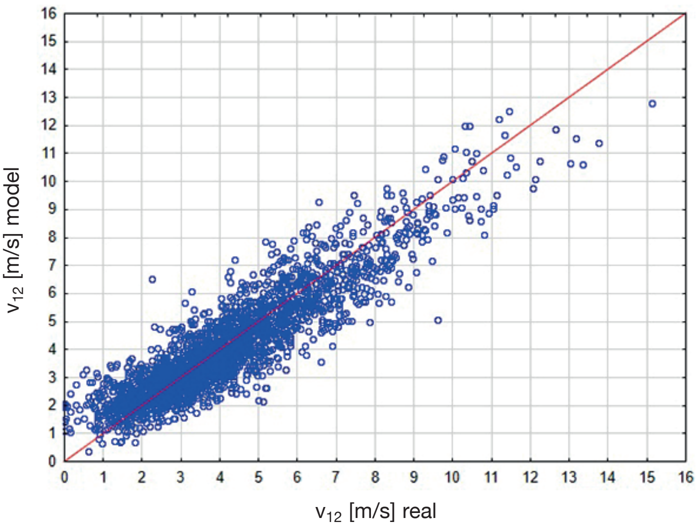

Fig. 7. Comparison of results from the model MLP 4:8:1 to the real dataset containing data for the period 2008–2009

Table 5
Data for calculation of wind profile exponent

Year	$v_{ave6m}[\mathrm{ms}^{-1}]$	$v_{ave12m}[\mathrm{ms}^{-1}]$	$\alpha[-]$
2008	3.77	4.27	0.18
2009	3.45	3.89	0.17
2008 and 2009	3.62	4.09	0.17

Table 6
Wind resource parameters on the different heights

Height a. g. l. [m]	$v_{ave}[\mathrm{ms}^{-1}]$	$\sigma_v[\mathrm{ms}^{-1}]$	$k\,[-]$	$c[\mathrm{ms}^{-1}]$	$p_w[\mathrm{Wm}^{-1}]$
10	4.19	2.00	2.12	4.50	70.0
12	4.32	2.06	2.13	4.67	77.9
20	4.71	2.25	2.18	5.17	103.5
30	5.05	2.41	2.21	5.60	130.0
40	5.39	2.53	2.23	5.95	154.8
50	5.51	2.62	2.25	6.21	174.6

6.2. Wind resource. The application of the artificial neural network to the input data allows for obtaining wind speed time series at 12 m a.g.l. (v_{12}, Fig. 2) in time range of 37 years ($2016 - 1979 = 37$). For further analysis, this series have to be recalculated to other heights, e.g.: 10 m, 20 m, 30 m, 40 m, and 50 m a.g.l. This can be done by eq. 3, following calculation of exponent α from eq. 4. Necessary data are presented in Table 5. Average wind speeds v_{ave6m} and v_{ave12m} (at 6 m and 12 m a.g.l.) are calculated, based on the measurements obtained from the meteorological station at Żelazna. Reanalysis data may not be used, because of the availability the wind speed value at 10 m a.g.l. only.

Despite notable differences between average speeds in particular years, the exponent alpha has almost the same value. For further calculations α is equal 0.17.

Table 6 presents average wind speeds at 10–40 m, as well as standard deviations σ_v, Weibull distribution coefficients k (eq. 11) and c (eq. 12), as well as wind power density p_w (eq. 14).

Linear regression charts, which were basis of Weibull distribution coefficients calculations are shown in Figs. 8–13. Distributions of wind speed at considered heights are presented in Figs. 14–19. All these figures were prepared in Octave software (www.octave.org).

Linear regression models, described by equations (presented in Figs. 8–13, describe the data very well, as the determination coefficients $R^2 = 0.98$ reach very high values. Therefore, wind speed distribution at the examined location may be described by Weibull distribution. It is clear that greater height moves the maximum of Weibull distribution to the right, towards higher wind speed (Figs. 14–19, Table 6). At this location, considerable fluctuations of wind speed occur. Table 6 shows that the

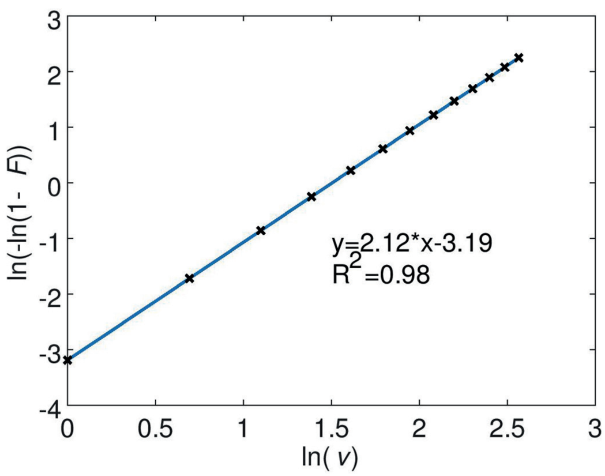

Fig. 8. Linear regression for the wind speed data at 10 m a. g. l.

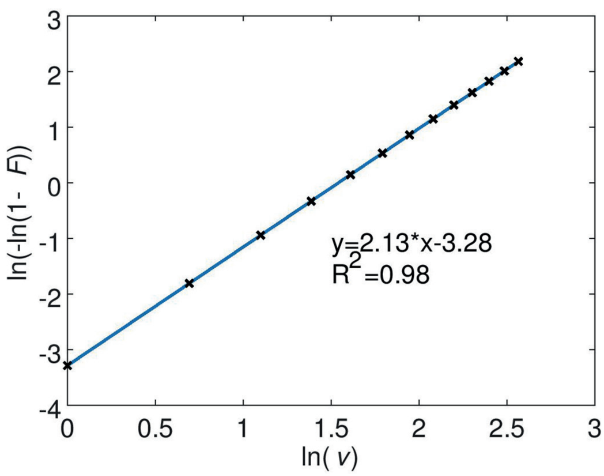

Fig. 9. Linear regression for the wind speed data at 12 m a. g. l.

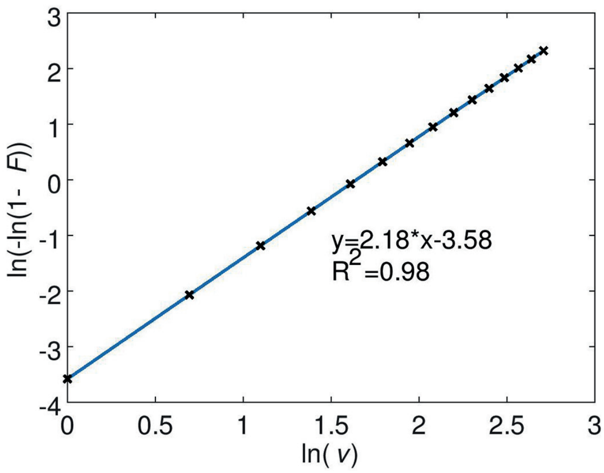

Fig. 10. Linear regression for the wind speed data at 20 m a. g. l.

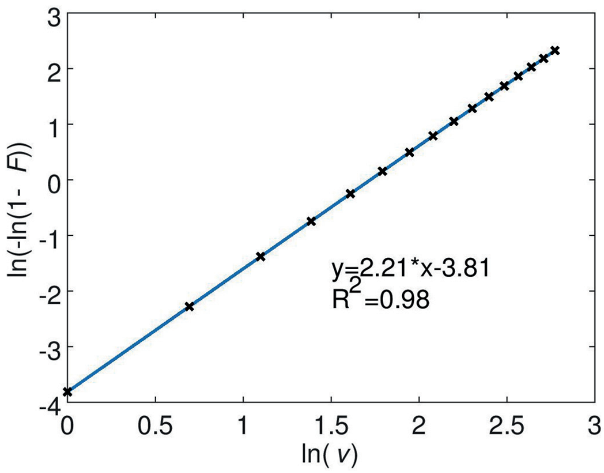

Fig. 11. Linear regression for the wind speed data at 30 m a. g. l.

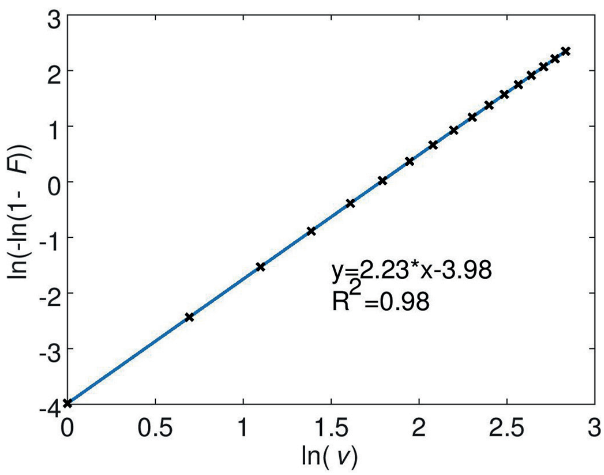

Fig. 12. Linear regression for the wind speed data at 40 m a. g. l.

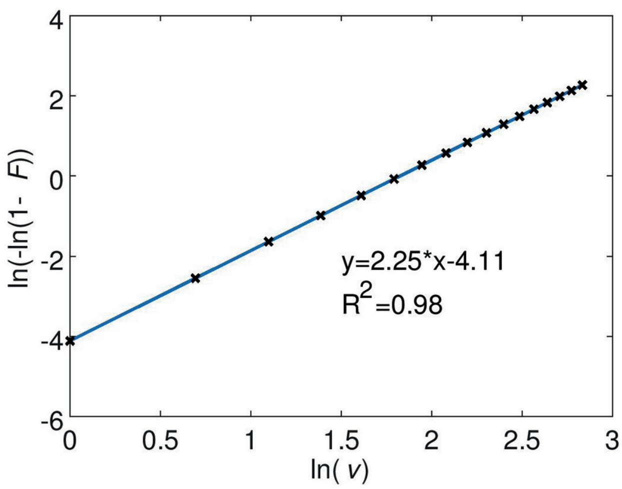

Fig. 13. Linear regression for the wind speed data at 50 m a. g. l.

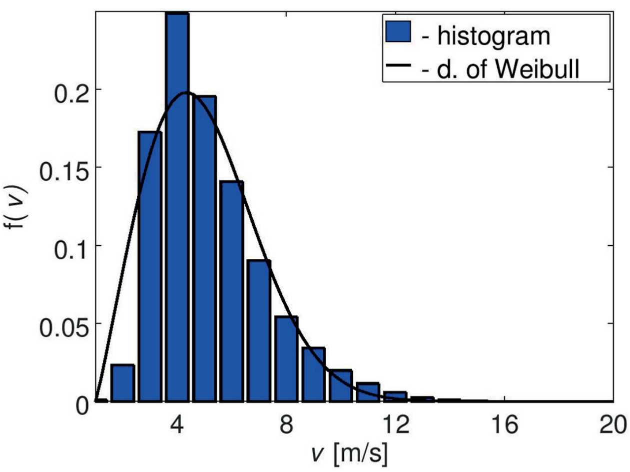

Fig. 14. Wind speed distribution at 10 m a. g. l.

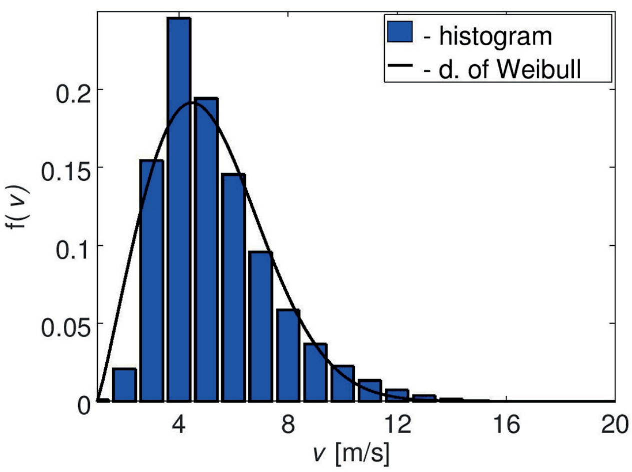

Fig. 15. Wind speed distribution at 12 m a. g. l.

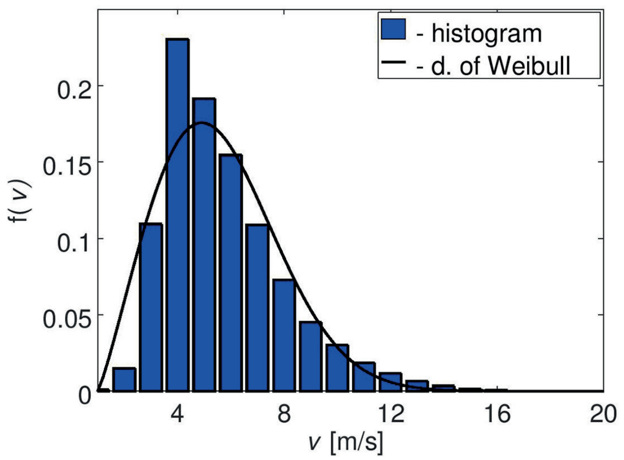

Fig. 16. Wind speed distribution at 20 m a. g. l.

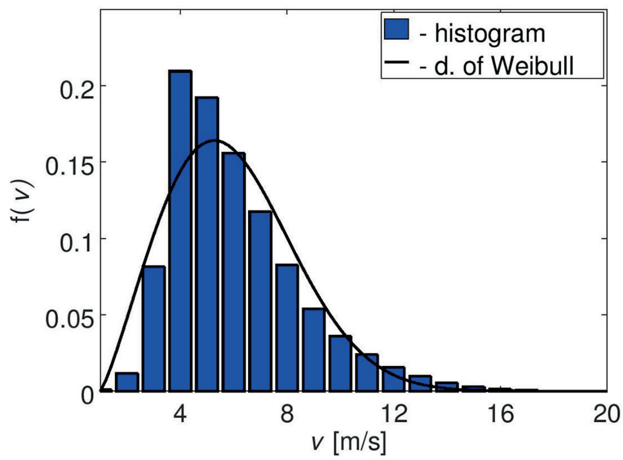

Fig. 17. Wind speed distribution at 30 m a. g. l.

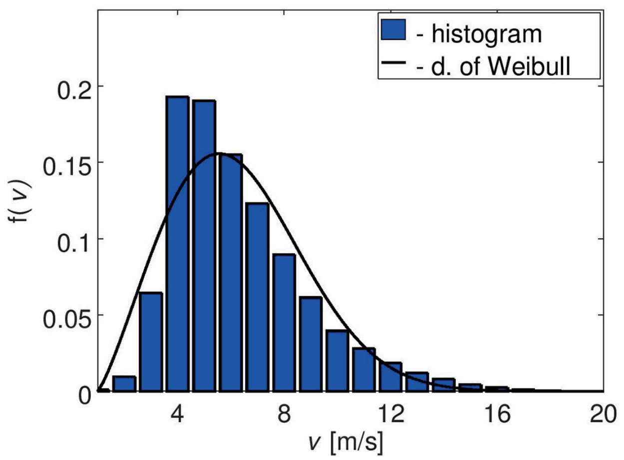

Fig. 18. Wind speed distribution at 40 m a. g. l.

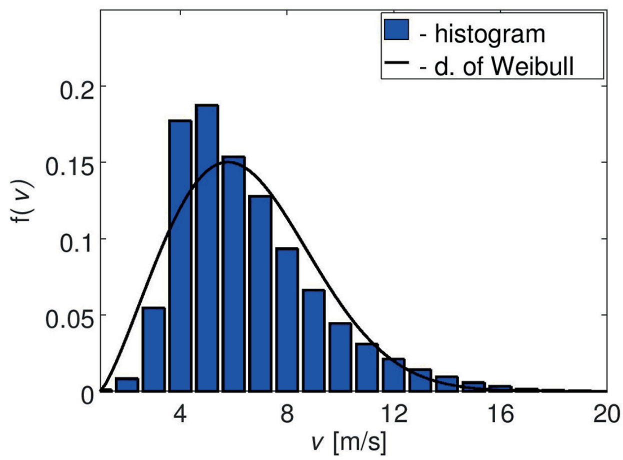

Fig. 19. Wind speed distribution at 50 m a. g. l.

value of standard deviation σ_v is close to half of the average speed v_{ave}. As a result, approximately 68% of all wind speed values lie within the range $< v_{ave} - 0.5v_{ave}; v_{ave} + 0.5v_{ave} >$. Close examination of the values v_{ave} and p_w from Table 6 may be useful for the evaluation of a given location towards its use for wind energy harvesting. The average wind power reaches quite low values, from 70 to 170 $\mathrm{Wm^{-1}}$, and it is at least twice lower than the value required in the USA, whereas the average wind speed is equal 4.21 $\mathrm{ms^{-1}}$ at 10 m a. g. l. and 5.51 $\mathrm{ms^{-1}}$ at 50 m a. g. l. The latter value fulfils UK requirements only. However, from the point of view of wind conditions in Poland, the examined location may be used for wind turbines.

7. Conclusions

The developed artificial neural model for the assessment of wind resources was positively verified, and it is characterized by good quality indexes (correlation coefficient for the test set above 0.9, and graph of distribution of the results from the model and the real measuring data is cumulative). Sensitivity analysis indicates that the most significant predictors (statistically) are (from the most to the least significant): wind speed at the reference station, day of year, temperature and air pressure on the day, with the first factor being 5 times more significant than the other factors. The graphs of dependencies between the predictors and wind speed in the point being analysed indicate that the dependence between wind speed at the reference station and the point being analysed is linear. Other predictors have smaller impact on the dependent variable, with temperature having directly proportional impact, and pressure having inversely proportional impact on the above mentioned variable.

Meteorological reanalysis is convenient data source for wind resource assessment, if there is no access to real long-term measurements from the local meteorological station. That was in this case. The measure – correlate – predict concept allows to restrict measurement campaign to only one or few years, which was applied to the examined location.

Łódź Hills have quite high fluctuations of wind speed. Wind speed distribution matches the Weibull distribution. The average power of wind is not as high as expected, it ranges from 70 to 170 Wm^{-1}. The average wind speed over 4.0 ms^{-1} means that this location can be useful for wind energy harvesting, form the point of view of Poland (local) wind conditions.

References

[1] J. Jurasz and J. Mikulik, "Economic and environmental analysis of a hybrid solar, wind and pumped storage hydroelectric energy source: a Polish perspective", *Bull. Pol. Ac.: Tech*. 65(6), 859–869 (2017).

[2] P.E. Morthorst, H. Auer, A. Garrad, and I. Blanco, "Wind Energy – The Facts, Part III The Economics of Wind Power", European Wind Energy Association, www.wind-energy-thefacts. org (2009). [Access date: 9 February 2018].

[3] C. Mone, M. Hand, M. Bolinger, J. Rand, D. Heimiller, and J. Ho, "2015 Cost of Wind Energy Review", Technical Report NREL/TP-6A20–66861, National Renewable Laboratory (2017). [Access date: 9 February 2018].

[4] EU Renewable Energy Directive 2009/28/EC, (2009).

[5] E. Hau, "Wind Turbines: Fundamentals, Technologies, Application, Economics", Springer (2006),

[6] A. Zaharim, S.K. Najid, A.M. Razali, and K. Sopian, "The Suitability of Statistical Distribution in Fitting Wind Speed Data", *WSEAS Transactions on Mathematics* 7, 718–727 (2008).

[7] L. Landberg, L. Myllerup, O. Rathmann, E.L. Petersen, B.H. Jørgensen, B.J. Niels, et al. "Wind resource estimation – an overview", *Wind Energy* 6, 261–71 (2003).

[8] T. Wizelius, "Developing Wind Power Projects: Theory and Practice", Taylor & Francis Ltd (2007).

[9] M.A. Lackner, A.L. Rogers, and J.F. Manwell, "The round robin site assessment method: A new approach to wind energy site assessment", *Renewable Energy* 33, 2019–2026 (2003).

[10] M. Zhang, "Wind Resource Assessment and Micrositing: Science and Engineering", Wiley (2015).

[11] "Atlas of the Republic of Poland" (in Polish), Principal Geodesist of Poland, Warsaw, (1993–1997).

[12] J. Kazak, J. van Hoof, and S. Szewranski, "Challenges in the wind turbines location process in Central Europe – The use of spatial decision support systems", *Renewable and Sustainable Energy Reviews* 76, 425–433 (2017).

[13] D. Czekalski, R. Korupczyński, and P. Obstawski, "Researching on the wind energy resources at the territory of Agricultural Experimental Institute of Warsaw University of Life Sciences at Żelazna" (in Polish), *Papers of Rzeszów University of Technology. Civil and Environmental Engineering*, 47, 63–70 (2008).

[14] E. Kalnay, M. Kanamitsu, R. Kistler, W. Collins, D. Deaven, L. Gandin, M. Iredell, S. Saha, G. White, J. Woollen, Y. Zhu, A. Leetmaa, and R. Reynolds, M. Chelliah, W. Ebisuzaki, W. Higgins, J. Janowiak, K.C. Mo, C. Ropelewski, J. Wang, R. Jenne, D. Joseph, "The NCEP/NCAR 40-Year Reanalysis Project", *Bull. Amer. Meteor. Soc*. 77, 437–471 (1996).

[15] F. Mesinger, G. DiMego, E. Kalnay, K. Mitchell, P.C. Shafran, W. Ebisuzaki, D. Jović, J. Woollen, E. Rogers, E. H. Berbery, M.B. Ek, Y. Fan, R. Grumbine, W. Higgins, H. Li, Y. Lin, G. Manikin, D. Parrish, and W. Shi, "North American Regional Reanalysis", *Bull. Amer. Meteor. Soc*. 87, 343–360 (2006).

[16] S. Szot and M. Kosowski, "A comparison of the radiosonde data and the data set basing on the NCEP-NCAR reanalysis" (in Polish), *Geographical Studies* 136, 31–44 (2014).

[17] D.P. Dee, S.M. Uppala, A.J. Simmons, P. Berrisford, P. Poli, S. Kobayashi, U. Andrae, M.A. Balmaseda, G. Balsamo, P. Bauer, P. Bechtold, A.C. M. Beljaars, L. van de Berg, J. Bidlot, N. Bormann, C. Delsol, R. Dragani, M. Fuentes, A.J. Geer, L. Haimberger, S.B. Healy, H. Hersbach, E.V. Hólm, L. Isaksen, P. Kållberg, M. Köhler, M. Matricardi, A.P. McNally, B.M. Monge-Sanz, J.-J. Morcrette, B.-K. Park, C. Peubey, P. de Rosnay, C. Tavolato, J.-N. Thépaut, and F. Vitart, "The ERA-Interim reanalysis: configuration and performance of the data assimilation system", *Q.J.R. Meteorol. Soc*. 137, 553–597 (2011).

[18] A. Derrick, "Development of the Measure Correlate Predict Strategy for Site Assessment", In European Community Wind Energy Conference, Proceedings of the 1993 International Conference, Lubeck-Travemunde, Germany, 8–12 March 1993, Garrad, A.D., Palz, W., Screller, S., Eds.; Stephens, H.S. and Associates: Bedford, UK, 681–685 (1993).

[19] A.L. Rogers, J.W. Rogers, and J.F. Manwell, "Comparison of the performance of four measure–correlate–predict algorithms", *Journal of Wind Engineering and Industrial Aerodynamics* 93, 243–264 (2005).

[20] S.M. Weekes, A.S. Tomlin, S.B. Vosper, A.K. Skea, M.L. Gallani, and J.J. Standen, "Long-term wind resource assessment for small and medium-scale turbines using operational forecast data and measure–correlate–predict", *Renewable Energy* 81, 760–769 (2015).

[21] M.L. Thøgersen, M. Motta, T. Sørensen, and P. Nielsen, "Measure- Correlate-Predict Methods: Case Studies and Software Implementation", Proceeding of European Community Wind Energy Conference (2007).

[22] S. Velazquez, J.A. Carta, and J. Matias, "Comparison between ANNs and linear MCP algorithms in the long-term estimation of the cost per kWh produced by a wind turbine at a candidate site: A case study in the Canary Islands", *Applied Energy* 88, 3869–3881 (2011).

[23] J. Zhang , S. Chowdhury, A. Messac, and B. Hodge, "Assessing Long-TermWind Conditions by Combining Different Measure-Correlate-Predict Algorithms", ASME. International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Vol. 3A: 39th Design Automation Conference (2013).

[24] S. Diaz, J.A. Carta, and J.M. Matias, "Comparison of several measure-correlate-predict models using support vector regression techniques to estimate wind power densities. A case study", *Energy Conversion and Management* 140, 334 – 354 (2017).

[25] J.A. Carta, S. Velázquez, and P. Cabrera, "A review of measurecorrelate- predict (MCP) methods used to estimate long-term wind characteristics at a target site", *Renewable and Sustainable Energy Reviews* 27, 362 – 400 (2013).

[26] S.M. Weekes, and A.S. Tomlin, "Data efficient measure-correlatepredict approaches to wind resource assessment for small-scale wind energy", *Renewable Energy* 63, 162–171 (2014).

[27] V. Borget, P.A. Monnier, and M. Strack, "Long-term Scaling of Site Measurements: Evaluation of Long-Term Meteorological Data in France and Comparison of Correlation Methods", *DEWI Magazin* 30, 61–68 (2007).

[28] D. Rajeev, D. Dinakaran, and S.C.E. Singh, "Artificial neural network based tool wear estimation on dry hard turning processes of AISI4140 steel using coated carbide tool", *Bull. Pol. Ac.: Tech*. 65(4), 553–559 (2017).

[29] M. Lefik, "Some aspects of application of artificial neural network for numerical modeling in civil engineering", *Bull. Pol. Ac.: Tech*. 61(1), 39–50 (2013).

[30] http://documentation.statsoft.com/STATISTICAHelp.aspx? path= SANN/Overview/SANNOverviewsTrainingofNeural Netowrks. [Access date: 9 February 2018].

[31] A. Rappaport, "Sensitivity Analysis in Decision Making", *The Accounting Review* 42, 441–456 (1967).

[32] A. Saltelli, M. Ratto, T. Andres, F. Campolongo, J. Cariboni, D. Gatelli, M. Saisana, and S. Tarantola, "Global Sensitivity Analysis. The Primer", John Wiley & Sons, (2008).

[33] S. Rehman, M. Shoaib, I. Siddiqui, F. Ahmed, M.R. Tanveer, and S.U. Jilani, "Effect of Wind Shear Coefficient for the Vertical Extrapolation of Wind Speed Data and its Impact on the Viability of Wind Energy Project", *Journal of Basic & Applied Sciences* 11, 90–100 (2005).

[34] L. Chapman, D.S. Hammond, and J.E. Thornes, "Roughness length estimation along road transects using airborne LIDAR data", *Meteorological Applications* 19, 420–426 (2012).

[35] J. Wieringa, "Updating the Davenport roughness classification", *Journal of Wind Engineering and Industrial Aerodynamics* 41, 357–358 (1992).

[36] M.L. Ray, A.L. Rogers, and J.G. McGowan, "Analysis of wind shear models and trends in different terrain", In: *Proceedings of American Wind Energy Association Windpower*, Pittsburgh, PA, USA; June 2006 (2006).

[37] C. Carrillo, J. Cidrás, E. Díaz-Dorado, and A.F. Obando-Montaño, "An Approach to Determine the Weibull Parameters for Wind Energy Analysis: The Case of Galicia (Spain)", *Energies* 7, 1–25 (2014).

[38] R. Gupta and A. Biswas, "Wind data analysis of Silchar (Assam, India) by Rayleigh's andWeibull methods", *Journal of Mechanical Engineering Research* 2, 010–024 (2010).

[39] P. Bhattacharya and R. Bhattacharjee, "A study on Weibull distribution for estimating the parameters", *Journal of Applied Quantative Methods* 5, 234 – 241 (2010).

[40] A. Parajuli, "A Statistical Analysis of Wind Speed and Power Density Based on Weibull and Rayleigh Models of Jumla, Nepal", *Energy and Power Engineering* 8, 271–282, (2016).

[41] D.L. Elliott, C.G. Holladay, W.R. Barchet, H.P. Foote, and W.F. Sandusky, "Wind Energy Resource Atlas of the United States, Wind power classes", (1986) http://rredc.nrel.gov/wind/pubs/atlas/tables/1–1T.html. [Access date: 9 February 2018].

[42] U.B. Gunturu and C.A. Schlosser, "Characterization of wind power resource in the United States", *Atmos. Chem. Phys*. 12, 9687–9702 (2012).

[43] A. Cramb, "Dagenham 'worst location for a wind turbine'", *The Telegraph*, 9 July 2009, http://www.telegraph.co.uk/news/earth/earthnews/5787111/ Dagenham-worst-location-for-a-wind-turbine.html. [Access date: 9 February 2018].

[44] "Europe's onshore and offshore wind energy potential. An assessment of environmental and economic constraints", European Environment Agency Technical Report (2009), 6, https://www.eea.europa.eu/publications/europes-onshoreand- offshore-wind-energy-potential. [Access date: 9 February 2018].

[45] M. Michalak, "Wind energy resource assessment for the needs of small wind energy" (in Polish). *AGH electrical and electronic engineering* 28, 14–19 (2009).

[46] A. Ostrowska-Bućko, "Wind energy utilisation based on small vertical axis wind turbines" (in Polish), *Civil and Environmental Engineering* 5, 65–72 (2014).