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Feasibility Assessment of a Wind Power Plant with Insufficient Local Wind Data Using Cascade-Correlating Neural Network

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The introduction of incentive schemes for wind power plants throughout most European countries has sparked a substantial growth in interest from investors. In rushing to qualify for their part of the approved quotas, investors may not properly evaluate their investments, causing some of them to be economically unjustifiable. When assessing wind power plant feasibility, a key factor is the historic wind data. It is used as the basis for selecting the type, number and layout of the wind turbines. Unfortunately, historic wind data for a potential wind power plant location is often scarce, meaning investors do not have the data needed for making valid decisions on the quality of potential wind power plant projects.

This paper describes a method for wind power plant output power estimation even if no historic wind data is available for the given location. A cascade correlation neural network is applied on wind characteristic measurements from remote locations. The results are verified by comparison of the predicted output power, obtained by using the proposed method, and already operational wind power plant with the actual values. A significant correlation exists between these two, confirming that the proposed method can be used as a robust tool for assessing the feasibility of potential wind power plant locations.

Ocjena isplativosti vjetroelektrane u slučaju nedovoljnih podataka o vjetru uporabom kaskadno-korelacijskih neuronskih mreža

Izvornoznanstveni članak

Uvođenje sustava poticaja za gradnju vjetroelektrana u većini europskih zemalja izazvalo je golem interes investitora. S obzirom na ograničene kvote, odnosno ukupno dopuštenu instaliranu snagu u vjetroelektranama, investitori često ne provode dovoljno detaljnu analizu investicije, što može imati za posljedicu donošenje pogrešnih odluka vezanih za odabir lokacije i instaliranu snagu buduće vjetroelektrane. Prilikom izrade studije isplativosti vjetroelektrane najvažniji ulazni podatak predstavljaju povijesni podaci vezani prvenstveno za brzinu i smjer vjetra. Na temelju tih se podataka odabire tip, broj i razmještaj vjetroagregata. Nažalost, tih podataka za veliki broj potencijalnih lokacija vjetroelektrana često nema, što znači da investitori ponekad nemaju na temelju čega provesti valjane analize.

Ovaj rad opisuje metodu za predviđanje izlazne snage vjetroelektrane na lokaciji za koju ne postoje povijesni podaci. Naime, kaskadno-korelacijske neuronske mreže primjenjuju se na povijesne podatke koji postoje za obližnje lokacije, na temelju čega se dobivaju podaci o značajkama vjetra za razmatranu lokaciju. Rezultati su potvrđeni i analizirani usporedbom predviđene izlazne snage vjetroelektrane dobivene proračunom, s poznatim vrijednostima izlazne snage stvarne vjetroelektrane. Potvrđen je visoki stupanj korelacije, što potvrđuje da se iznesena metoda može koristiti kao alat za procjenu isplativosti potencijalnih lokacija vjetroelektrana.

Keywords
Cascade-correlating algorithm
Neural networks
Feasibility assessment
Wind power plan

Ključne riječi
Kaskadno-korelacijski algoritam
Neuronske mreže
Ocjena isplativosti
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1. Introduction

Throughout the last two decades, wind power has been experiencing an extreme growth. In 2010, the worldwide installed wind power capacity broke the 200 GW barrier, with a growth rate of 27,8 %, as shown in Figure 1 [1]. China and the USA established themselves as the world's leaders in installed wind power capacity, and reached 35 and 26 GW of installed wind capacity respectively. The leading European country is Germany, with over 25 GW of wind power capacity installed [2].

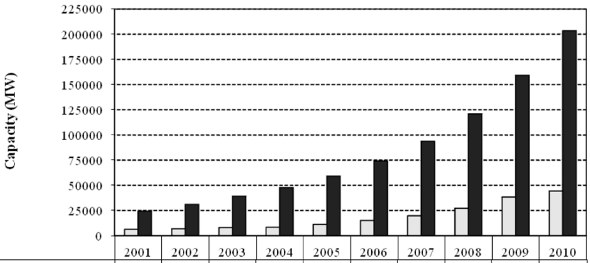
The primary reason for such an enormous interest in wind power plants are the various incentive schemes.

Most schemes can be classified in one of the following [3]:

- a fixed feed-in tariff scheme,
- a feed-in premium scheme,
- a quota scheme.

Symbols/Oznake

c_p	- level of aerodynamic transformation - stupanj aerodinamične pretvorbe	$P_{wind(0)}$	- average wind power at the sea level - prosječna snaga vjetra na razini mora
$c_{p,max}$	- Betz' limit - Betzov koeficijent	R	- gas constant - plinska konstanta
$E_{k, wind}$	- kinetic energy of the wind - kinetička energija vjetra	t	- time - vrijeme
p	- absolute pressure - apsolutni tlak	T	- temperature - temperatura
P_t	- transformed power - transformirana snaga	v	- speed - brzina
P_{wind}	- average wind power - prosječna snaga vjetra	ρ	- air density - gustoća zraka



	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
New Capacities (MW)	6282	6859	8114	8398	11331	15127	19776	27261	38312	44287
Overall Capacity (MW)	24322	31181	39295	47693	59024	74122	93930	120903	159213	203500

Figure 1. New and overall installed wind power plant capacities in the world

Slika 1. Novi i ukupno instalirani kapaciteti vjetroelektrana u svijetu

Investors compete for their part of the installed wind capacity quotas specified by each country. This is especially the case with countries with partly congested transmission network. Therefore, some investors tend to rush into inadequately elaborated projects with unclear feasibility studies. The most important information needed to correctly assess the feasibility of a wind power plant project is the historic wind data. Wind characteristics should be available for at least the past year in order to make a valid feasibility assessment of the project, and correctly select the type, number and layout of the wind turbines. Some countries do not maintain the required wind characteristics data for the investors' potential wind power plant locations. Therefore, the investors have to set up their own measurement masts and collect data for at least one year. This causes a significant prolongation of the project unbeneficial to the investor.

This paper addresses the described problem by introducing a method for wind power plant project assessment when there are no available historical wind measurements for the exact location. The method is based on wind data available from locations relatively near to the location lacking such data.

The rest of this paper is organized as follows: The following section describes the data needed for accurate wind power plant location assessment. Section 3 provides a brief overview of the wind prediction methods and describes neural networks including a literature overview. Section 4 provides a thorough description of the measurement locations, equipment, and the data on which the neural network is trained. Section 5 provides the calculation results, and conclusions are discussed in Section 6.

2. Input Data

In order to successfully predict the wind power plant's output power, it is imperative to first identify the parameters which directly influence wind power plant operation. Wind turbine blades transform kinetic energy of the wind into mechanical energy on the turbine rotor, which is coupled with an electrical generator via a common shaft. The produced wind power density is proportional to the air density (ρ) and the cubed wind speed. For a constant wind speed, it can be calculated as:

$$P_{wind} = \frac{\rho v^3}{2}. \tag{1}$$

In general, the wind speed is not constant. Thus, the average wind power density for a given time interval is equal to:

$$P_{wind} = \frac{1}{2T}\int_0^T \rho v^3 \left(t\right) \mathrm{d}t. \tag{2}$$

The density of dry air can be calculated using the ideal gas law, expressed as a function of the atmospheric pressure and air temperature:

$$\rho = \frac{p}{R \cdot T}. \tag{3}$$

The specific gas constant for dry air is 287,05 J/kgK. Air pressure and temperature are functions of the height above the sea level. At sea level (ρ = 1,2 kg/m^3), the wind power density can be approximated as $P_{\text{wind}(0)} = 0{,}6 \cdot v^3$.

Wind kinetic energy over time t is calculated according to:

$$P_{\text{wind}(0)} = 0{,}6 \cdot v^3. \tag{4}$$

and for the time interval T with constant wind power speed:

$$E_{\text{k,wind}} = \int_0^t P_{\text{wind}}(t)\,\mathrm{d}t, \tag{5}$$

Since wind still has a significant speed even after it passes through the wind turbine blades, all its kinetic energy cannot be transformed into mechanical energy. This is known as the Betz' law and can be mathematically expressed as a level of aerodynamic transformation (coefficient of performance), which is defined as the ratio of the mechanical rotor power and the wind power:

$$E_{\text{k,wind}} = \frac{1}{2}\rho v^3 T. \tag{6}$$

The largest theoretical value for the aerodynamic transformation level (maximum coefficient of performance) is $c_{\text{p,max}}$ = 16/27 = 0,593 (Betz' limit), and the efficiency of any given wind power plant facility cannot be greater than that value. Taking all the energy transformation losses within a wind turbine into consideration, it can be concluded that less than half of the total kinetic energy of the wind can be transformed in useful electrical energy, as shown in Figure 2.

From all of the above, it can be concluded that wind speed and direction data, as well as air temperature and pressure data are the necessary parameters for calculating the wind power plant's power output [4].

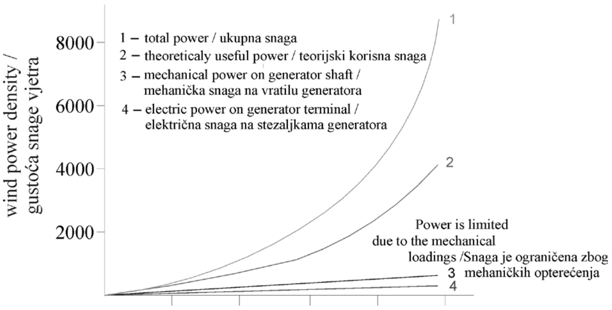


Figure 2. Curve of transformation of wind energy to electricity

Slika 2. Krivulja pretvorbe energije vjetra u električnu energiju

3. Neural Networks

3.1. Wind-prediction Methods

The wind speed prediction methods can be arranged in two categories: the physical methods and the statistical methods.

In order to predict wind speed physical methods use physical considerations such as weather forecast, terrain structure, temperature and pressure. Some of these methods are Numerical Weather Forecast and Mesoscale models.

The concept of statistical methods is based on finding the relationship of the observed wind speed time series. The most common statistical method is autoregressive integrated moving average (ARIMA).

However, many methods use both physical and statistical parameters.

3.2. Cascade-correlating Neural Networks

A neural network is a non-linear statistical data modeling tool. Its computational structure resembles a biological neuron [5], and its ability to learn from experience makes it appealing and sought solution for various problems [6]. Neural networks learn from the available data and examples by pursuing an input-output mapping without an explicit model equation statement [7].

Cascade neural networks using a cascade-correlating algorithm were developed by Fahlman and Libiere [8] in 1990. The main characteristic of this method is the addition of a new neuron into a hidden layer during the network learning process [9], as shown in Figure 3. The initial network contains only input and output layers. New (hidden) layers are used only during the learning process. The network is considered upgraded when an optimal architecture is achieved with an optimal number of hidden layers.

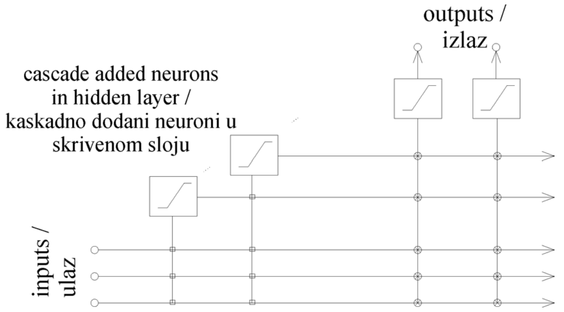


Figure 3. Neural network upgraded with cascade-correlating algorithm

Slika 3. Neuronska mreža s kaskadno-korelacijskim algoritmom

A self-organizing network with an optimized number of neurons in the hidden layers is obtained this way. The learning time is much shorter, making these networks faster. Additionally, they are very robust and results are obtained even with a fairly small number of input parameters. Optimization is performed by minimizing the Mean Squared Error (MSE) between the real network output and the calculated output [10].

Neural networks are suitable for modeling complex nonlinear processes [11-14]. This is the reason they are widely used in wind power generation forecasting based on meteorological data. The most important works include [15], where a non-linear recursive least-squares method is used to train a recurrent neural network. In [16] neural network models are reported to have better performance than regression modeling in wind power turbine generation estimation. In [17] a neural network is applied to estimate power output as a function of the time delay of wind speed and the power itself, while [18] is focused on virtual and generalized models to predict turbine parameters of interest.

3.3. Activation Function Selection

For selecting the most suitable transfer function inside the cascade-added neurons, it is necessary to explore the dependence of the wind turbine power output on the wind speed, as well as other characteristics. Dependence of wind turbine power output on air density and thus on air temperature and pressure is expressed in (1) – (4). True functional dependence of wind speed and wind turbine power output is provided in a form of the power curve, which is supplied by the wind turbine manufacturer. Although this data is different across various types of turbines, they all have the same shape. In Figure 4 the Siemens SWT-2.3-93 wind turbine power curve is shown. The shape of the curve fits into a hyperbolic tangent function, which is therefore chosen as an activation function for the cascade added elements in neural networks. The general function of hyperbolic tangent is:

$$\tanh(z) = \frac{\sinh(z)}{\cosh(z)} = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}} = \frac{e^{2z} - 1}{e^{2z} + 1}. \tag{7}$$

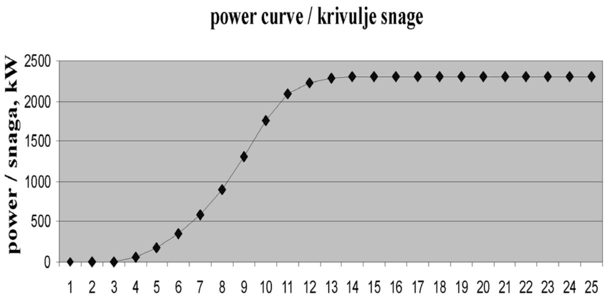


Figure 4. Siemens SWT-2.3-93 wind turbine power curve
Slika 4. Krivulja snage vjetroagregata Siemens SWT-2.3-93

4. Data Collection and Analysis

4.1. Selection of Input and Output Data

The output from the neural network is the wind power plant's active power, more precisely the power output at the grid connection point. Formulae (2) – (5) state that the required input parameters are the wind speed and direction, as well as the parameters which define air density (temperature and pressure). Therefore, it is necessary to define [19]:

- wind speed and direction,
- air temperature and pressure.

Thus, the training of the network requires a sequence of input data that defines the atmospheric parameters and the associated output data sequence that defines the active power at generator terminals.

4.2. Wind Measurements

Measurements of wind speed and direction, as well as the air temperature and pressure, are mostly obtained by meteorological masts [20]. Since their wind turbine shafts are situated relatively high above the ground, greater accuracy and correlation can be achieved between wind potential and output power (Figure 4). This paper is based on the processed data from 50 m tall towers [21- 22].

4.3. Measurement Locations

The observed wind power plant location is the location of the actual WPP Trtar-Krtolin near the city of Šibenik with the rated power of 11,2 MW. WPP Trtar-Krtolin is connected to the grid at the nearby substation 220/110/30 kV Bilice over a 30 kV cable line and line field where power measurements and feed-in energy audits are made. Several 50 m meteorological masts measuring wind speed and direction, as well as air temperature and pressure are erected in the vicinity of the WPP's location. Three locations were chosen to carry out measurements: Krš-Pađene, Borajica and Promina. The positions of these locations with their respective distances to WPP Trtar-Krtolin are provided in Figure 5. It can be seen that the meteorological mast locations are significantly far from each other. The idea of this paper is to show a significant correlation between the measurements from these distant measurement mast locations and the electricity produced at WPP Trtar-Krtolin.

All the data include time records for suitable inter-comparisons and synchronization. At Krš-Pađene, wind speed was measured at 25 m and 50 m above the ground, and the wind direction at 50 m above the ground. At Borajica and Promina, wind speed was measured at 10, 30, 44 and 46 m, with the wind direction at 10 and 44 m, the air temperature at 2 and 40 m, and the atmospheric pressure at 2 m above the ground. The measurement equipment used at Krš-Pađene, Promina and Borajica are cup anemometers, wind wanes, thermometers and barometers.

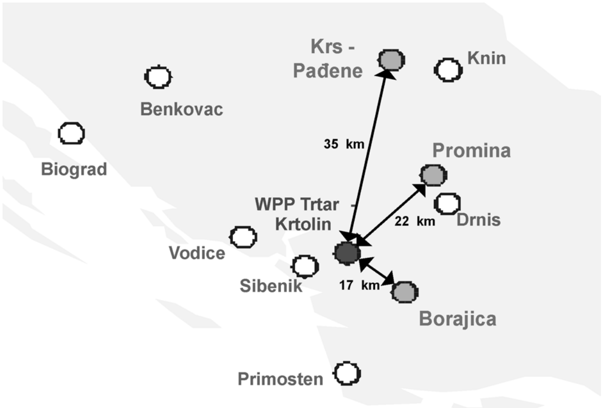


Figure 5. Positions of wind mast locations

Slika 5. Lokacije stupova za mjerenje značajki vjetra

The input data from these locations used by the training algorithm are given in Tables 1, 2 and 3.

Table 1. Input parameters of location Krš-Pađene (measuring location A)

Tablica 1. Ulazni parametri lokacije Krš-Pađene (mjerna lokacija A)

Label / Oznaka	Value / Vrijednost	Height / Visina
A-V1	wind speed / brzina vjetra, m/s	50 m
A-V2	wind speed / brzina vjetra, m/s	25 m
A-S1	wind direction / smjer vjetra	50 m

Table 2. Input parameters of location Borajica (measuring location B)

Tablica 2. Ulazni parametri lokacije Borajica (mjerna lokacija B)

Label / Oznaka	Value / Vrijednost	Height / Visina
B-V1	wind speed / brzina vjetra, m/s	10 m
B-V2	wind speed / brzina vjetra, m/s	30 m
B-V3	wind speed / brzina vjetra, m/s	44 m
B-V4	wind speed / brzina vjetra, m/s	46 m
B-S1	wind direction / smjer vjetra	10 m
B-S1	wind direction / smjer vjetra	44 m
B-T1	air temperature / temperatura zraka, °C	40 m
B-P1	air pressure / tlak zraka, hPa	2 m

The measuring devices at Krš-Pađene are calibrated according to NIST standards, while those at Promina and Borajica according to MEASNET standards. All measurements at these three locations were recorded as 10-minute averages. At the same time, the active power output was recorded at WPP Trtar-Krtolin, more precisely in substation Bilice. The power output records are 15-minute averages.

Table 3. Input parameters of location Promina (measuring location C)

Tablica 3. Ulazni parametri lokacije Promina (mjerna lokacija C)

Label / Oznaka	Value / Vrijednost	Height / Visina
C-V1	wind speed / brzina vjetra, m/s	10 m
C-V2	wind speed / brzina vjetra, m/s	30 m
C-V3	wind speed / brzina vjetra, m/s	44 m
C-S1	wind speed / brzina vjetra, m/s	10 m
C-S2	wind direction / smjer vjetra	44 m
C-T1	air temperature / temperatura zraka, °C	40 m
C-P1	air pressure / tlak zraka, hPa	2 m

4.4. Neural-network training

The output result (wind power plant power output at the grid connection point) is given as an hourly average and is synchronized with the input data. A set of 3290 simultaneous hourly averages are selected corresponding to 137 days (around 4 and a half months). Increasing this number would not only increase the network accuracy, but also the network training time. The algorithm selects an optimal neural network by minimizing the MSE of the output values. This optimized network with a certain number of cascade-added elements in hidden layer represents the final result of the algorithm and can be used for wind power plant power output estimation in the future.

5. Results

The results are obtained by a neural network with 70 cascade-added elements in the hidden layer. The calculation was terminated after 22238 iterations. The best network with the least MSE was selected in iteration number 13285. Behavior of MSE through calculation iterations is shown in Figure 6.

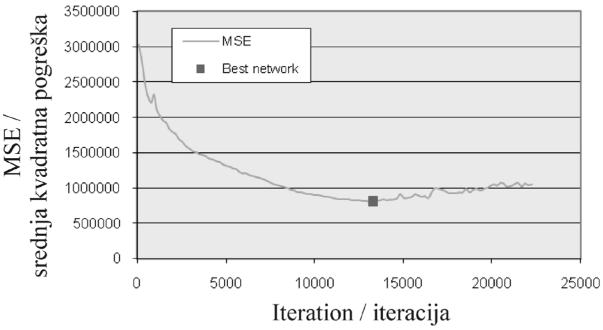


Figure 6. Mean squared error (MSE) during calculation iterations

Slika 6. Srednja kvadratna pogreška tijekom iteracija

The correlation factor is r = 0,9423 (R^2 = 0,8878). The actual and forecasted values are both displayed in Figure 7.

Figure 8 shows the scatter plot of the actual vs. forecasted power with a correlation factor of 0,9423. Since there are 3290 data points, Figure 9 shows a three day period subset in more detail.

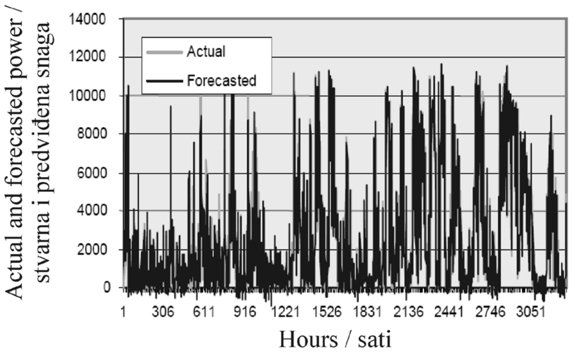


Figure 7. Actual and forecasted values of WPP power output in a period of 137 days

Slika 7. Stvarne i predviđene vrijednosti izlazne snage vjetroelektrane tijekom 137 dana

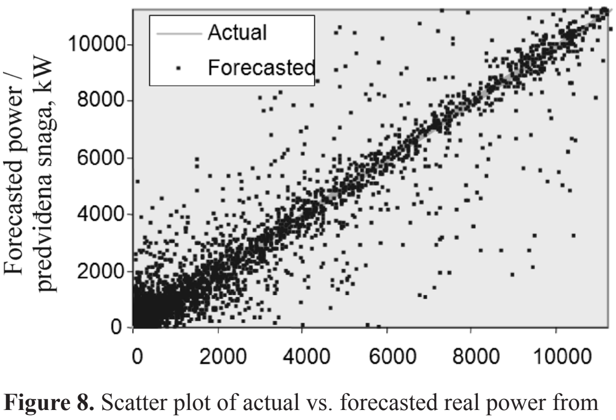


Figure 8. Scatter plot of actual vs. forecasted real power from WPP Trtar-Krtolin

Slika 8. Stvarne i predviđene vrijednosti izlazne snage vjetroelektrane Trtar-Krtolin

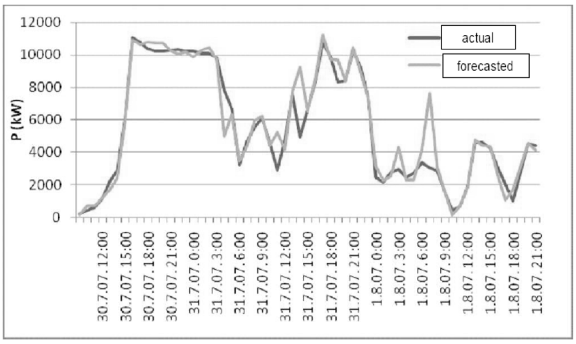


Figure 9. Actual and forecasted values of WPP Trtar-Krtolin power output in a 3 day time period

Slika 9. Stvarne i predviđene vrijednosti izlazne snage vjetroelektrane Trtar-Krtolin tijekom 3 dana

The difference between the measured and estimated power is shown in Figure 10. Input importance (InpIm) of every input value was also calculated. When calculating the input importance, each of the input values is deleted from the model sequentially and the effect of this action on the predicting model qualities is calculated.

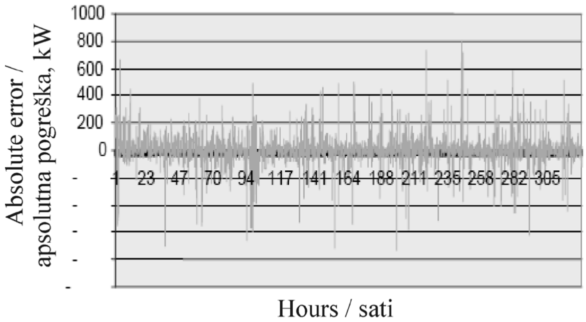


Figure 10. The difference between the measured and estimated power

Slika 10. Razlika između stvarne i predviđene vrijednosti izlazne snage vjetroelektrane Trtar-Krtolin

The most important input values are given in Table 4.

Other input values have InImp values between 4 and 5%. It can be seen from InImp results that value with label A-V1, more precisely wind speed at 50 m above the ground, at Krš-Pađene has the highest input importance. This is expected since wind measurements should be made at heights close to the heights of wind turbine shaft. In this way, the measurement accuracy is increased.

Also, it should be stressed that given measuring location toward location of WPP Trtar-Krtolin is situated in direct north-northeast wind trajectory of dominant wind direction in wider area. This can be viewed from wind rose measured on subject measuring location (Figure 11). Mean annual wind speed at this location is in the range of 4,5-6,5 m/s and wind power 350-700 W/m^2 [23].

Table 4. Input importance of the most influential input values on a quality of model

Tablica 4. Prikaz najvažnijih ulaznih podataka

Label / Oznaka	Input Importance Value / Vrijednost ulaznog podatka
A-V1	16,8 %
C-S2	8,8 %
C-S1	7,1 %

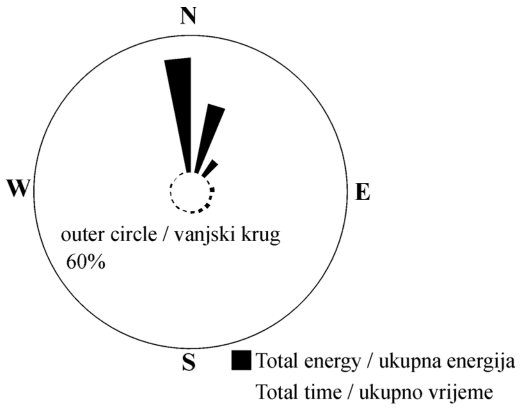


Figure 11. Wind rose at location Krš-Pađene

Slika 11. Ruža vjetrova na lokaciji Krš-Pađene

Large influence of measuring location Krš-Pađene on surrounding area is the result of the fact that other two values measured on the same location also have bigger InpIm values (Table 5).

6. Conclusions

The described method was used to assess wind power plant power output on the basis of atmospheric and wind characteristic data measured in the surroundings of the future wind power plant. Regarded method represents very useful tool from a statistic view considering a very good correlation of forecasted and real data measured on the existing wind power plant location.

Table 5. Input importance of values measured at location at location Krš-Pađene

Tablica 5. Prikaz važnosti mjernih podataka lokacija Krš-Pađene

Label / Oznaka	Input Importance Value / Vrijednost ulaznog podatka
A-V1	16,8 %
A-V2	5,9 %
A-S1	4,6 %

The benefit of the described method is that it does not require long term on-site measurements in order to assess the quality of wind power plant location. As it was described in the example, very good correlation results can be expected already after 4 months of wind characteristics measurements available from other locations. With the increase in number of input values accuracy of wind power plant location assessment will also be increased.

This wind power plant location assessment tool is very robust and can be used on other wind farm locations using data from wind measuring masts in the location vicinity. Such situations will occur very often in Šibenik County where a large number of potential wind power plant locations was already put in spatial plans and a large number of wind masts was erected.

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