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Wind speed modeling in wind energy based on one year of SCADA data using statistical distribution functions

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ABSTRACT

Wind speed is one of the basic meteorological parameters in the field of wind energy, as it directly affects the efficiency and output power of wind turbines. Wind speed distribution is most often modeled using statistical functions, in particular the probability density function (PDF) and the cumulative distribution function (CDF). In this paper, a comparison of several statistical distributions (Weibull, Rayleigh, gamma, normal and beta) was performed through the analysis of the empirical distribution of wind speed recorded over a one-year period. For all distributions, the root mean square error (RMSE) and the mean absolute error (MAE) between observed and modeled values were calculated, and the smallest values of these criteria were used to identify the model that most accurately describes the actual wind behavior at the observed location. The obtained results enable a more precise assessment of the wind speed distribution and the energy potential of the location, which is of key importance for optimizing the operation of wind energy systems.

KEYWORDS

Wind speed, Statistical modeling, Probability density function, Cumulative distribution function, RMSE, MAE

1. INTRODUCTION

Winds are a significant component of the climate system and are closely intertwined with our daily lives. They vary over a wide range of spatial and temporal scales, from global to regional winds, to locally smaller turbulent eddies [1]. The energy sector is under increasing pressure to address the chal- lenges of climate change and the growing demand for energy. In this context, the transition to sustainable and environmentally friendly en- ergy sources has become essential for long-term stability and develop- ment [2]. Wind energy is one of the fastest growing renewable energy sources (RES) that have been developed as an efficient response to growth and global economic development over the decades [3]. Wind energy, a renewable energy source, is becoming increasingly popular and is among the priority investment areas for many countries [4].

Although the benefits of harnessing wind energy are obvious, implementation can be subject to a number of practical difficulties and uncertainties, one of which is the intermittent and unstable nature of wind [5]. The chaotic nature of wind speed poses modeling difficulties [6]. Wind energy availability and conversion efficiency depend on the distribution of wind speed [7]. The distribution of wind speed is of great importance in the assessment of wind resources, and not just the average wind speed. In order to adequately describe the variation of wind energy, it is necessary to fit various probability functions to field data, and therefore the distribution of wind energy is represented by standard statistical functions [8]. The global transition to sustainable energy has become imperative due to the rapid depletion of fossil fuel resources and the serious environmental consequences associated with greenhouse gas emissions [9].

Wind energy represents one of the key directions of development of renewable energy sources, aimed at reducing emissions of harmful gases and increasing energy efficiency. The efficiency of wind power plants is significantly determined by the characteristics of the wind, with wind speed representing a key parameter in assessing the energy potential of a location and selecting the optimal wind turbine. Since wind energy is proportional to the cube of wind speed, it means that even a small increase in wind speed results in a large increase in wind energy, therefore the most important factor affecting wind energy is wind speed [10]. SCADA (Supervisory Control and Data Acquisition - SCADA) is a control system architecture that uses computers, networked data transmission, and graphical user interfaces for high-level process control [11]. Wind farms are connected to a SCADA system to continuously collect wind turbine data [12].

The main factors affecting wind speed and direction are the pressure gradient force, the Coriolis force, and friction with the Earth's surface [13]. Since wind speed is a random variable that varies in time and space, its statistical modeling is of key importance for the accurate assessment of wind energy potential. For this purpose, various statistical distributions are applied, with the Weibull, Rayleigh, gamma, normal, and beta distributions being the most commonly used. Their characteristics are analyzed using the probability density function and the cumulative distribution function. To assess the quality of fitting theoretical distributions to empirical data, statistical error criteria are used, including RMSE and MAE. These indicators quantitatively measure the deviation between empirical and theoretical distribution values, with smaller RMSE and MAE values indicating a better fit of the model to the actual data. Accordingly, the distribution with the smallest values of these criteria is considered the most appropriate for describing the actual behavior of wind speed at the observed location.

The aim of this paper is to conduct a detailed comparative analysis of multiple statistical distributions based on one-year wind speed measurements, with a special emphasis on identifying the model that most accurately describes the empirical data and best approximates the actual wind speed distribution at the observed location. By comparing different theoretical distribution functions and adapting them to experimental data, a deeper understanding of wind characteristics and its variability during the year is gained. The obtained results contribute to increasing the accuracy of wind energy potential estimation, which is crucial for proper planning and dimensioning of wind energy plants. At the same time, they provide guidelines for more efficient management and optimization of wind energy systems, with the aim of achieving maximum energy efficiency and economic justification of investments. The scientific contribution of this paper is reflected in the comparative analysis of multiple statistical distributions based on real SCADA data, with the application of RMSE and MAE criteria for selecting the optimal wind speed distribution model.

2. METHODOLOGY

2.1. Location and description of the wind farm

The wind speed data used in this paper were collected at the Rudine wind farm in Croatia. The wind farm is located at Rudine, at an altitude ranging from 280 to 400m above sea level. The initial project planned the construction of 34 wind turbines, of which 12 wind turbines have been completed so far, along with the accompanying infrastructure in the form of access roads and operational plateaus. The project amendments envisage a reduction in the total number of wind turbines to 18, while at the same time reducing the area of the aforementioned infrastructure. The location of the existing and planned wind power plant "Rudine" is shown in Figure 1 [14].

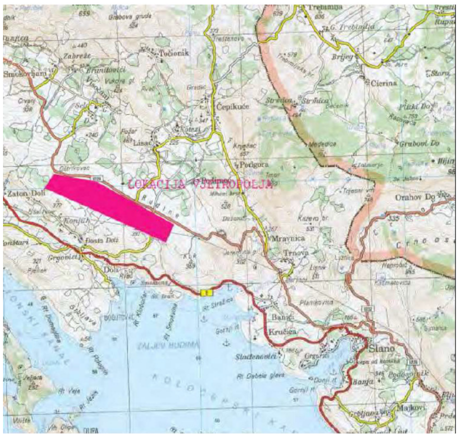

Figure 1: Location of the existing and planned wind power plant "Rudine"

The planned location of the wind turbines within the "Rudine" wind power plant is shown in Figure 2 [14].

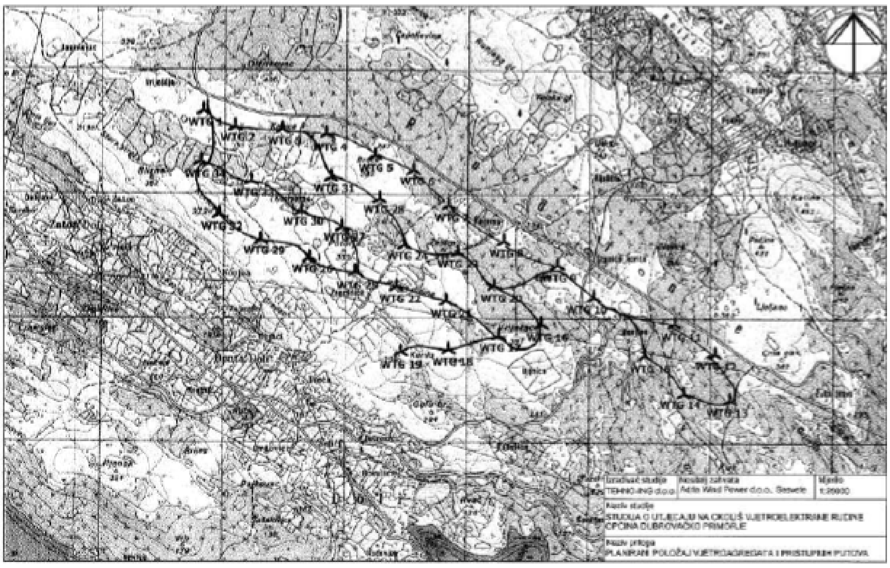

Figure 2: Planned location of wind turbines within the "Rudine" wind farm

2.2. Data collection

The wind turbines are connected to a SCADA system, which enables continuous collection of operational data. Wind speed measurements were made using an anemometer placed at a height of 85m above the ground, with a time resolution of 10 minutes. A total of 630113 measurements were collected over a one-year period. For the purposes of analysis, a representative set of 63013 records was formed using equidistant sampling, with every tenth data point selected.

The paper analyzes wind speeds collected from the WTG 27 wind turbine. Based on these data, statistical processing and modeling of the wind speed distribution was performed using several theoretical functions, including Weibull, Rayleigh, gamma, normal and beta distributions. Each distribution is defined by an appropriate set of parameters, the estimation of which allows for a precise description of the statistical characteristics of the wind speed.

2.3. Model evaluation

To assess the quality of the fit of theoretical distributions to empirical data, statistical error criteria were used, including root mean square error (RMSE) and mean absolute error (MAE), with smaller values of these criteria indicating better agreement of the model with the actual data. Analysis of probability density functions and cumulative distribution functions allows identification of the distribution that most accurately describes the empirical wind speed distribution and provides a reliable basis for assessing the wind energy potential of the observed location.

3. MATHEMATICAL FUNDAMENTALS OF DISTRIBUTION FUNCTIONS

Statistical distributions are a key tool for quantitative modeling and analysis of variable natural phenomena, with wind speed being one of the most important parameters in the field of wind energy. For each distribution, a probability density function and a cumulative distribution function can be determined.

Wind energy applications require accurate resource estimation, which can be achieved by a probability density function that describes the behavior of the wind [15]. Probability density functions (PDFs) are mathematical functions that characterize the likely behavior of a data set. This data set can correspond to the behavior of a random variable that is continuous in time. Since wind speed is a random variable, it is convenient to describe it using PDFs [16]. The probability density function $f(x)$ of a continuous random variable X is the first derivative of the cumulative distribution function $F(x)$ and is represented by the following equation [17]:

$$f(x)=\frac{d}{dx}F(x) \tag{1}$$

The cumulative distribution function for a random variable X is the mathematical function $F_X : R \rightarrow [0,1]$, which associates with each real number x the probability that the random variable X will take a value less than or equal to that value. The cumulative distribution function is represented by the following equation [17]:

$$F_X(x) = \Pr\,(X \leq x) \tag{2}$$

where:

$F_X(x)$ - cumulative distribution function of a random variable X, and Pr ($X \leq x$) - denotes the probability that X takes on a value less than or equal to x.

The mathematical foundations of the distribution functions for Weibull, Rayleigh, gamma, normal, and beta distributions are presented below.

3.1. Weibull distribution

The most commonly used statistical approach to predict the distribution of wind speed data is the Weibull probability density function. The Weibull distribution is a distribution with greater sensitivity and greater flexibility than other distributions [18]. The two-parameter Weibull and Rayleigh distributions are widely used as statistical methods in modeling wind speed data [6]. Currently, the two- or three-parameter Weibull distribution is widely used in wind energy engineering to estimate the expected level of electricity generation [19].

The Weibull distribution is often applied in wind energy because of its ability to model different forms of wind speed distribution. The probability density function of a two-parameter Weibull distribution is represented by the following equation [20]:

$$f(x)=\frac{\beta}{\eta}\left(\frac{x}{\eta}\right)^{\beta-1} e^{-\left(\frac{x}{\eta}\right)^{\beta}}, \beta>0, \eta>0 \tag{3}$$

where:

η - scale parameter and β - shape parameter.

The cumulative function of the two-parameter Weibull distribution is represented by the following equation [21]:

$$F(t)=1-\exp\left[-\left(\frac{t}{\alpha}\right)^{\beta}\right], t\geq 0 \tag{4}$$

where:

$F(t)$ - probability that the random variable T (wind speed) takes on a value less than or equal to t, $t \geq 0$ - values for which the function is defined, α - scale parameter and β - shape parameter.

The scale parameter determines the horizontal stretching of the distribution, with a larger value of the scale parameter resulting in a wider range of values. The shape parameter determines the shape of the distribution.

3.2. Rayleigh distribution

The probability density function of the Rayleigh distribution is represented by the following equation [22]:

$$f(x;a)=\frac{x}{\alpha^2} e^{-\frac{x^2}{2\alpha^2}} \tag{5}$$

The cumulative Rayleigh distribution function is represented by the following equation [22]:

$$F(x)=\int_0^x f(y)dy=\frac{1}{\alpha^2}\int_0^x ye^{-\frac{y^2}{2\alpha^2}}dy=\int_0^{\frac{x^2}{2\alpha^2}} e^{-z}dz=1-e^{-\frac{x^2}{2\alpha^2}} \tag{6}$$

where:

x - variable from the set of real positive numbers and α - scale parameter.

3.3. Gamma distribution

The probability density function of the gamma distribution is represented by the following equation [23]:

$$f(x_i)=\frac{1}{scale^{shape}\Gamma(shape)} x_i^{(shape-1)} e^{-\left(\frac{x_i}{scale}\right)} \tag{7}$$

where:

x_i - random variable, *shape* - gamma distribution shape parameter ($k > 0$), *scale* - gamma distribution scale parameter ($\Theta > 0$) and G(*shape*) - gamma function.

The cumulative gamma distribution function is represented by the following equation [22]:

$$F(x)=\int_0^x f(x)dx=\frac{a^b}{\Gamma(b)}\int_0^x u^{b-1}e^{-au}du=\frac{a^b}{\Gamma(b)}\int_0^{ax}\left(\frac{v}{a}\right)^{b-1}e^{-v}\frac{dv}{a}=\frac{1}{\Gamma(b)}\int_0^{ax}v^{b-1}e^{-v}dv=\frac{\gamma(b,ax)}{\Gamma(b)} \quad (8)$$

where:

x - random variable, *f*(*u*) - probability density function of gamma distribution, *a* - rate parameter, *b* - shape parameter, *Γ*(*b*) - gamma function and *γ* (*b, ax*) - incomplete gamma function.

3.4. Normal distribution

The probability density function of a normal distribution is represented by the following equation [22]:

$$f\left(x;\mu,\sigma^2\right)=\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \quad (9)$$

where:

x - random variable, *μ* - location parameter and *σ* - standard deviation.

A normal distribution with a location parameter equal to zero and a standard deviation *σ* = 1 is called a standard normal distribution. The cumulative function of the standard normal distribution is represented by the following equation [22]:

$$F(z)=\begin{cases}\frac{1}{2}+\frac{1}{2}P\left(\frac{1}{2},\frac{z^2}{2}\right) & \text{if } z\geq 0\\ \frac{1}{2}-\frac{1}{2}P\left(\frac{1}{2},\frac{z^2}{2}\right) & \text{if } z<0\end{cases} \quad (10)$$

where:

F(*z*) - cumulative distribution function of the standard normal distribution, *P* (*a, x*) - regularized incomplete gamma function, *z* - standardized value (*z* = (*x*-*μ*) / *σ*) indicates how far a value *x* is from the mean *μ*, expressed in units of standard deviation *σ*.

The incomplete gamma function is a gamma function bounded by an upper bound of x. The term "regularized" means that the function is scaled (normalized) to the interval [0,1], so that its value can be viewed as a probability or a relative fraction of the area under the density function.

3.5. Beta distribution

The probability density function of the beta distribution is represented by the following equation [22]:

$$f(x;\mathrm{p},\mathrm{q})=\frac{1}{B(p,q)}x^{p-1}(1-x)^{q-1} \quad (11)$$

where:

p - parameter of form 1, (*p* > 0), *q* - parameter of form 2, (*q* > 0), *x* - variable satisfying the condition 0 ≤ *x* ≤ 1, *B* (*p*, *q*) – denotes the beta function defined over the gamma distribution as *B* (*p*, *q*) = *Γ*(*p*)*Γ*(*q*)/*Γ*(*p*+*q*).

The beta distribution with parameters *p* = *q* = 1 reduces to a uniform distribution between zero and one. The cumulative beta distribution function is represented by the following equation [22]:

$$F(x)=\frac{1}{B(p,q)}\int_0^x t^{p-1}(1-t)^{q-1}dt=\frac{B_x(p,\mathrm{q})}{B(p,q)}=I_x(p,q) \quad (12)$$

where:

B_x, I_x - incomplete beta functions.

4. STATISTICAL DATA ANALYSIS

The wind speed data used in this paper were collected at the Rudine wind farm in Croatia. The wind farm is located at Rudine, at an altitude ranging from 280 to 400 m. Wind speed measurements were made using an anemometer placed at a height of 85 m above the ground, with a time resolution of 10 minutes. A total of 630,113 measurements were collected over a one-year period.

For the purposes of the analysis, a representative set of 63,013 records was formed using equidistant sampling, with every tenth data point selected. This approach allows for a reduction in the volume of data while maintaining the representativeness of the analyzed set.

The analysis was performed on data from the WTG 27 wind turbine, collected via the SCADA system.

Based on the formed data set, statistical processing and modeling of the wind speed distribution were performed using several theoretical distribution functions, including Weibull, Rayleigh, gamma, normal and beta distributions. Each of the above distributions is defined by a corresponding set of parameters whose estimation enables the description of the statistical characteristics of wind speed.

In order to assess the quality of the fit of theoretical distributions to empirical data, statistical error criteria were used, namely RMSE and MAE. These indicators allow a quantitative assessment of the deviation between empirical and theoretical values, with smaller RMSE and MAE values indicating better agreement of the model with the actual data.

In the Weibull distribution, it is necessary to determine the shape parameter (c) and the scale parameter (b) in order to calculate the probability density function and the cumulative function. To calculate the shape parameter, it is necessary to previously determine the value of the standard deviation (σ) and the mean wind speed ($\bar{u}$) based on a representative data set formed by equidistant sampling. To calculate the scale parameter (b), it is necessary to determine the mean wind speed over a one-year period and previously calculate the shape parameter (c).

When calculating the probability density function and the cumulative function of the Rayleigh distribution, the values of the wind speed and the scale parameter (α) are used. The scale parameter (α) is calculated using the mean wind speed ($\bar{u}$) and the constant π.

When calculating the probability density function and the cumulative gamma distribution function, it is necessary to first determine the values of the shape parameter (k) and the scale parameter (Θ). The shape parameter (k) is obtained by dividing the arithmetic mean of all values by the sample standard deviation, and then squaring the resulting value. The scale parameter (Θ) is obtained by dividing the sample variance by the arithmetic mean of the sample, where the variance is the square of the standard deviation.

After determining the mean wind speed and the sample standard deviation, the probability density function and the cumulative normal distribution function can be calculated.

The probability density function and the cumulative beta distribution function can be calculated after determining the values of the shape parameter 1 (parameter p), the shape parameter 2 (parameter q), the lower bound for the beta distribution (minimum of the interval x_{min}) and the upper bound for the beta distribution (maximum of the interval x_{max}).

In order to assess the deviation between the empirical and theoretical distribution values, statistical error measures are used. In this paper, the measures Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were applied. These measures allow a quantitative assessment of the accuracy of the distribution model in relation to the observed data. RMSE is represented by the following equation [24]:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{13}$$

where:

$\hat{y}_i$ - value of empirical cumulative distribution function, y_i - value of cumulative Weibull distribution function and n - sample size.

MAE is represented by the following equation [24]:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{14}$$

Smaller values of RMSE and MAE indicate better agreement between the theoretical model and empirical data. Therefore, the distribution with the smallest values of these criteria is considered the most appropriate for describing the statistical characteristics of wind speed at the observed location.

5. GRAPHIC AND STATISTICAL ANALYSIS OF WIND SPEED DISTRIBUTION

In order to assess the agreement of different statistical distributions with real (empirical) wind speed data, a graphical analysis was first performed. The application of graphical analysis in wind speed modeling in wind energy using different distribution functions is an important step that allows for a direct assessment of the agreement of theoretical distributions with real data and the detection of deviations in certain parts of the wind speed range.

The wind speed histogram, together with the theoretical probability density function curves of different distributions, visually shows the extent to which the theoretical distributions approximate the empirical data. After the visual assessment, a quantitative comparison was performed using RMSE and MAE, which allows for a precise determination of the degree of agreement of each theoretical distribution with the real data. In this way, the combination of graphical and numerical analysis provides a comprehensive insight into the quality of wind speed modeling and identifies the distributions that best describe the empirical distribution.

The wind speed histogram, together with the theoretical probability density function curves of the Weibull, Rayleigh, gamma, normal and beta distributions, is shown in Figure 1.

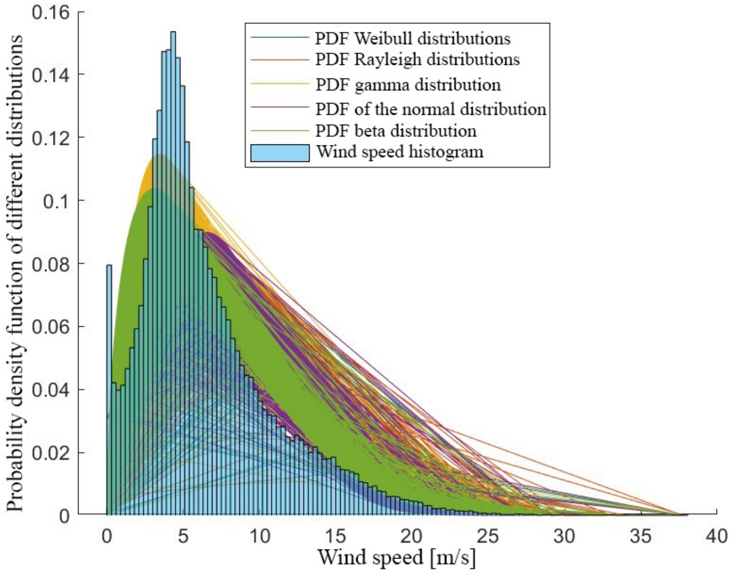

Figure 1: Histogram of wind speeds and curves of theoretical probability density functions of Weibull, Rayleigh, gamma, normal and beta distributions

In Figure 1, the wind speed histogram shows the frequency of occurrence of certain wind speed values in the observed period. The theoretical probability density functions of various statistical distributions, shown in Figure 1 together with the wind speed histogram, represent mathematical models that describe the probability of occurrence of certain wind speeds. The heights of the probability density functions of various statistical distributions show the probability that wind speeds are in a certain interval, with a higher height of the function indicating a more frequent occurrence of the corresponding wind speeds.

The position of the peak of the probability density function of different statistical distributions corresponds to the most frequent values of wind speed. The width of the probability density function of different statistical distributions shows the range of variations of wind speed, while the end points (tails) of the function reflect the frequency of extreme values of wind speed, i.e. very low or very high speeds.

Comparative analysis of the graphical representations in Figure 1 allows us to assess the degree of compliance of individual distributions with real data, in particular with regard to the shape of the curve, its width and the position of the maximum of the probability density function. This comparison allows us to determine the distribution that most accurately approximates the empirical characteristics of wind speeds at the observed location.

The central part of the wind speed histogram, shown in Figure 1, is most accurately approximated by the probability density functions of the beta and normal (Gaussian) distributions, as confirmed by the values RMSE = 0.3963 for the beta distribution and RMSE = 0.3964 for the normal distribution. Based on the MAE value, the Rayleigh distribution (MAE = 0.2317) best approximates the wind speed histogram.

Although the Weibull distribution is often used in wind speed analysis, in this case it did not show the best agreement with the empirical data, which can be attributed to its limited flexibility in describing more complex distribution shapes. On the other hand, the beta and normal distributions better approximate the middle part of the distribution, while the Rayleigh distribution gives better results in terms of average deviation, which is confirmed by the RMSE and MAE values. Distributions such as the Weibull and gamma distributions achieve higher MAE values, which indicates their lower suitability for describing empirical data.

For the purpose of modeling wind speeds in wind energy, it is necessary to show a comparison of the empirical cumulative wind speed distribution function with the theoretical cumulative functions of the Weibull, Rayleigh, gamma, normal and beta distributions.

Figure 2 shows the empirical cumulative wind speed distribution function along with the theoretical cumulative Weibull, Rayleigh, gamma, normal and beta distribution functions.

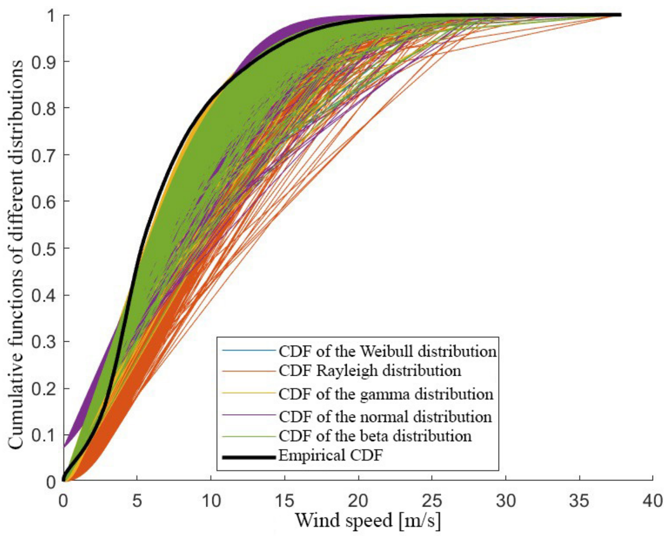

Figure 2: Empirical cumulative wind speed distribution function and theoretical cumulative functions of Weibull, Rayleigh, gamma, normal and beta distributions

The empirical cumulative distribution function of wind speed (empirical CDF) shows the distribution of actually recorded wind speeds. Theoretical cumulative distribution functions show the expected distribution of wind speed values according to the selected statistical distribution (Weibull, Rayleigh, gamma, normal and beta).

The selected theoretical cumulative distribution function shows very good agreement with the empirical cumulative distribution function of wind speed when the deviation between the empirical cumulative distribution function of wind speed and the corresponding theoretical cumulative distribution function is minimal. If the empirical cumulative distribution function of wind speed deviates significantly from the theoretical cumulative functions of all considered distributions, it can be concluded that the selected theoretical cumulative distribution functions do not correspond to the actual data and inadequately approximate the wind speed distribution. In this case, it is necessary to select and apply another theoretical cumulative distribution function in order to achieve a more precise approximation of the actual data.

RMSE and MAE values for different types of distributions are shown in Table 1.

Table 1: Values of RMSE and MAE for different types of distributions

Distribution	RMSE	MAE
Weibull	0.399373271	0.469061626
Rayleigh	0.432387968	0.231695971
Gamma	0.403777638	0.480526376
Normal (Gaussian)	0.396430335	0.395770709
Beta	0.396315358	0.475081171

Analysis of RMSE values shows that the beta distribution and the normal distribution best approximate the empirical cumulative wind speed distribution function shown in Figure 2, almost equally accurately, with the differences in agreement between the theoretical and empirical values being minimal. The MAE values show that the Rayleigh distribution best approximates the empirical cumulative wind speed distribution function shown in Figure 2.

6. CONCLUSION

In this paper, a comparative analysis of five statistical distributions (Weibull, Rayleigh, gamma, normal and beta) was performed in order to model the wind speed distribution based on empirical SCADA data. The analysis included a graphical comparison of probability density functions and cumulative distribution functions, as well as a quantitative evaluation using the statistical criteria RMSE and MAE.

The research results show that the beta and normal distributions achieve the lowest RMSE values, which indicates the best agreement with the empirical cumulative distribution function. On the other hand, the Rayleigh distribution shows the smallest MAE value, indicating the smallest average absolute deviation from the actual data. These results confirm that the choice of the optimal distribution depends on the evaluation criteria, and that different distributions may be more suitable for different aspects of modeling.

Based on the conducted analysis, it can be concluded that the application of statistical distribution functions represents an effective approach in modeling wind speed and assessing wind energy potential. The application of appropriate distributions contributes to the reduction of technical and economic uncertainties, optimization of system operation and achieving higher energy efficiency.

The limitation of this work is reflected in the analysis of data from one location and one time period, which may affect the general applicability of the obtained results. Future research may include the analysis of longer time series of data, as well as the comparison of a larger number of locations in order to obtain more comprehensive conclusions.

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