



UDC 53

EDN KCMRY

<https://www.doi.org/10.33910/2687-153X-2026-7-3-144-151>

Wind power variations in time domain: Introducing a waiting time probabilistic distribution

V. Ximenes ¹, A. F. Belo ¹, K. Shimakawa ²

¹ East Timor National University, Av. Cidade de Lisboa, Díli, East Timor

² Gifu University, 1–1 Yanagido, Gifu 501-1193, Japan

Authors

Vital de Jesus Ximenes, ORCID: 0009-0005-7998-1415, e-mail: ximenesvital5@gmail.com

Abelito Filipe Belo, ORCID: 0000-0003-1759-9470, e-mail: abelitofilipe@gmail.com

Koichi Shimakawa, e-mail: koichi@gifu-u.ac.jp

For citation: Ximenes, V., Belo, A. F., Shimakawa, K. (2026) Wind power variations in time domain: Introducing a waiting time probabilistic distribution. *Physics of Complex Systems*, 7 (3), 144–151.
<https://www.doi.org/10.33910/2687-153X-2026-7-3-144-151> EDN KCMRY

Received 11 May 2026; reviewed 19 June 2026; accepted 22 June 2026.

Funding: The present work was performed at the Cooperation Unit of the Faculty of Engineering, UNTL.

Copyright: © V. Ximenes, A. F. Belo, K. Shimakawa (2026). Published by Herzen State Pedagogical University of Russia. Open access under CC BY License 4.0.

Abstract. Time-dependent changes in wind speed (WS) observed at different locations in East Timor and Japan are analyzed using a statistical approach in the time domain. The WS histogram is approximated to be the Weibull distribution at two different locations. The reason why the histogram follows the Weibull distribution will be discussed through a generalization of the Rayleigh distribution which has been originally applied to the scattering of the electromagnetic wave. It is also found that the waiting time probability density for WS, defined as the time spent by the wind speed below or above a given threshold value, is presented by a power-law scaling with time as $t^{-\alpha}$ ($\alpha < 2.5$), which will be associated with long-term correlations, but not a Poisson-type distribution. A new concept of fractional dynamics within the stochastic analysis of WS will be presented.

Keywords: wind power, stochastic approach, waiting time distribution, Weibull distribution, fractional dynamics

Introduction

Wind power should be a major energy source for maintaining sustainable environmental conditions on the globe (Hasche 2010; Joselin et al. 2007). However, wind power is inherently unstable, and the power produced by turbines fluctuates significantly over time. Therefore, it is necessary to understand the characteristic features of these variations through the establishment of standard analytical techniques, regardless of location. There are two primary approaches to analyzing wind characteristics, namely analyses in the time and the frequency domains (Apt 2007; Bucaneg, Wan 2002; Liu et al. 2016; Murthy, Rahi 2014).

In the time domain, a simple way is to construct a statistical histogram of the wind speed (Bucaneg, Wan 2002; Murthy, Rahi 2014) and to apply variogram time-series analysis (Liu et al. 2016). It is well known that the wind speed histogram follows the Weibull distribution (Matsfelt, Davidson 2018; Murthy, Rahi 2014). In the frequency domain, the frequency spectrum (FS) helps to elucidate detailed features associated with periodicity (Apt 2007).

In the present study, we investigate WS in the time domain at two different locations: near the seaside in East Timor and on the mountain side in Japan. At both locations, the wind speed histogram is well approximated by the Weibull distribution. The reason why the histogram follows the Weibull distribution is discussed in terms of a generalization of the Rayleigh distribution which has been originally applied to the scattering of the electromagnetic wave (Hofmann, Okafor 2001; Muller et al. 2002). We further examine the waiting time statistics, defined as the time during which the wind speed remains below or above a given threshold value. To our knowledge, the waiting time distribution $\Psi(t)$ for wind speed has not yet been fully understood. We find that $\Psi(t)$ follows a power-law scaling with time as $t^{-\alpha}$ ($\alpha < 2.5$), indicating the presence of long-term correlations rather than a correlated Poisson-type distribution.

Experimental

We measured wind speed (WS) variations in the time domain at two different locations. One site was the Hera campus, located 10 km east of the Díli city, East Timor (8.55° S latitude, 125.56° E longitude), where measurements were conducted from June to September 2019. Wind speed was measured using a 6-m instrumented tower equipped with a 600 W wind generator (Nantong R&X Energy Technology: RX-600H3). The output voltage of the wind turbine was recorded every 100 s by a data logger, yielding a total of $N_T = 74398$ (Belo, Shimakawa 2021).

The second WS dataset was obtained at the Takayama Field Station of the River Basin Research Center, Gifu University. The station is located on a high mountainside at an elevation of 1,342 m at 36°8' N latitude and 137°26' E longitude in Gifu, Japan. The observation site lies within a basin characterized by a complex topography, and the instrument is installed in an open area of approximately 1,100 m², surrounded by evergreen coniferous trees about 20 m in height. Wind speed was measured using a propeller anemometer (Young 05103-47) mounted at a height of 4.2 m. The data were sampled every 10 mins from January 2008 to December 2017 (for 10 years), yielding a total of $N_T = 525,600$ data points.

Results

Fig. 1 shows the time variation of the wind speed $v(t)$, measured every 100 s over three months (June — September 2019) at the Hera campus. Before proceeding to the discussion of our main focus area, i. e., the waiting-time statistics of wind speed, to get overall features of wind power, we first discuss the histogram for the wind speed $v(t)$ in which the probability density at a particular wind speed is obtained. The number of occurrences of each speed N is counted for this project.

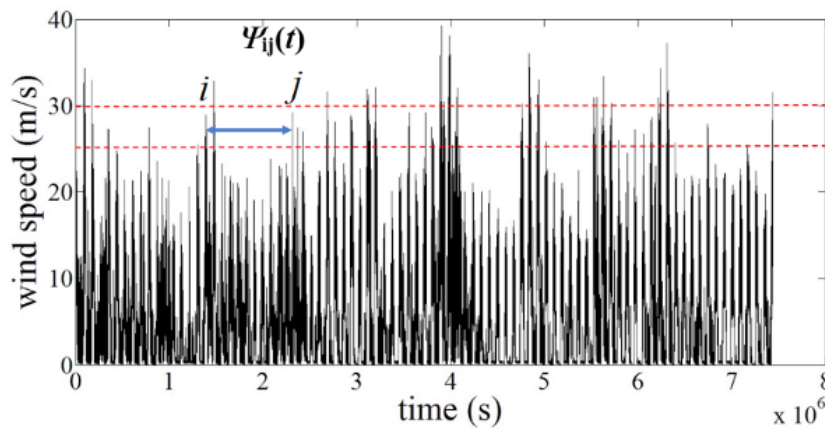


Fig. 1. Time-variation of the wind speed $v(t)$, measured every 100 s over three months at the Hera campus. Waiting time t_{ij} is defined as the time interval between the i -th and j -th events within a selected velocity range, for example, $25 \leq v < 30$ (red dashed lines)

Discrete bars shown in Fig. 2 represent the normalized wind speed distribution, N/N_T , where $N_T = 74,398$ is the total number of data points. It is well known that the Weibull distribution is widely accepted and commonly used for wind data analysis (Matsfelt, Davidson 2018; Murthy, Rahi 2014).

We therefore examine whether the wind speed follows the Weibull distribution, as shown by the solid red line and given as

$$W(v) = A \frac{k}{c} \left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^k\right], \quad (1)$$

where k is the shape parameter, c is the scale parameter (with the same units as wind speed, ms^{-1}), and A is the fitting parameter.

The solid line in Fig. 2 represents the probability density $W(v)$ (equation (1)), obtained using the parameters $A = 1.35$, $c = 11.5$, and $k = 2.1$. This model reproduces the experimental observation reasonably well ($R^2 = 0.82$), although the histogram itself shows some scatters. Note that the well-known Rayleigh distribution corresponds to the special case, $k = 2.0$ (Hofmann, Okafor 2001; Muller et al. 2002).

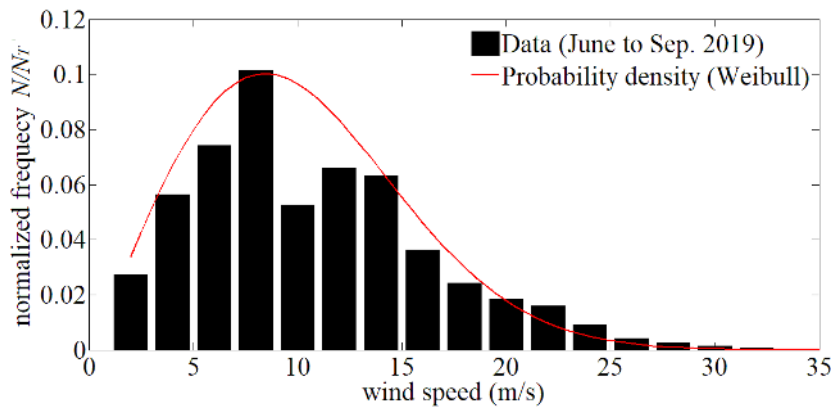


Fig. 2. Normalized wind speed distribution (histogram) and the Weibull distribution at the Hera campus with fitting parameters ($A = 1.35$, $c = 11.5$, $k = 2.1$) ($R^2 = 0.82$)

Let us now discuss how to define the waiting time distribution (WTD) for a particular wind speed, as shown in Fig. 1. From the waiting time t_{ij} , i. e., the time interval between the i -th and j -th events within a selected velocity range between v and $v + dv$, the waiting time probability density $\Psi_{ij}(t)$ between the i -th and j -th events can be deduced from the number of occurrences N_v (histogram) divided by the total number of events (N_{vt}) in a manner similar to the wind speed distribution (see Fig. 2). In the following, we present the experimentally obtained $\Psi(t)$ (normalized event number), discussing their scientific insight in Section IV.

Fig. 3 shows the *normalized* histogram (dots) of waiting time, i. e., N_v/N_{vt} , which is defined as the waiting time probability density $\Psi(t)$ (s^{-1}) (solid line), for $v < 5$ (a), $5 \leq v < 10$ (b), $10 \leq v < 15$ (c), $15 \leq v < 20$ (d), $20 \leq v < 25$ (e), and $v \geq 25$ (f). $\Psi(t)$ is approximately given by a power law as

$$\Psi(t) = C t^{-\alpha}, \quad (2)$$

where C is a constant, t is time (s), and α is a numerical parameter. The fitting parameters are listed in Table 1. It is found that the value of α is approximately 2, except for $v \geq 25$ m/s. The reason why $\Psi(t)$ follows a power law will be discussed in Section IV.

Let us now discuss WS in another place (Takayama, Japan). Fig. 4 shows the WS histogram (a) for the period 2008–2017 (10 years), with a total number of data points $N_T = 526,027$, obtained in the same manner as in Fig. 2 (Hera campus), and (b) for 2017 (1 year), with a total number of data points $N_T = 52,560$. There is no significant difference between (a) and (b) in Fig. 4, suggesting that climate change found globally cannot be affected for the Weibull parameters A , c , and k (see figure caption) between 2017 and the period of 2008–2017.

Let us now turn to the waiting time probability density $\Psi(t)$ (s^{-1}). Fig. 5 shows the waiting time histogram (dots) and the waiting time probability density $\Psi(t)$ (s^{-1}) (solid line for fitting) at Takayama (Japan): (a) for $v < 0.25$, (b) for $0.25 \leq v < 0.5$, (c) for $0.5 \leq v < 1.0$ and (d) $v \geq 1.0$. Similar to the Hera campus results, $\Psi(t)$ (s^{-1}) is also well approximated by a power law (see equation (3)). The fitting parameters for Fig. 5 are listed in Table 2.

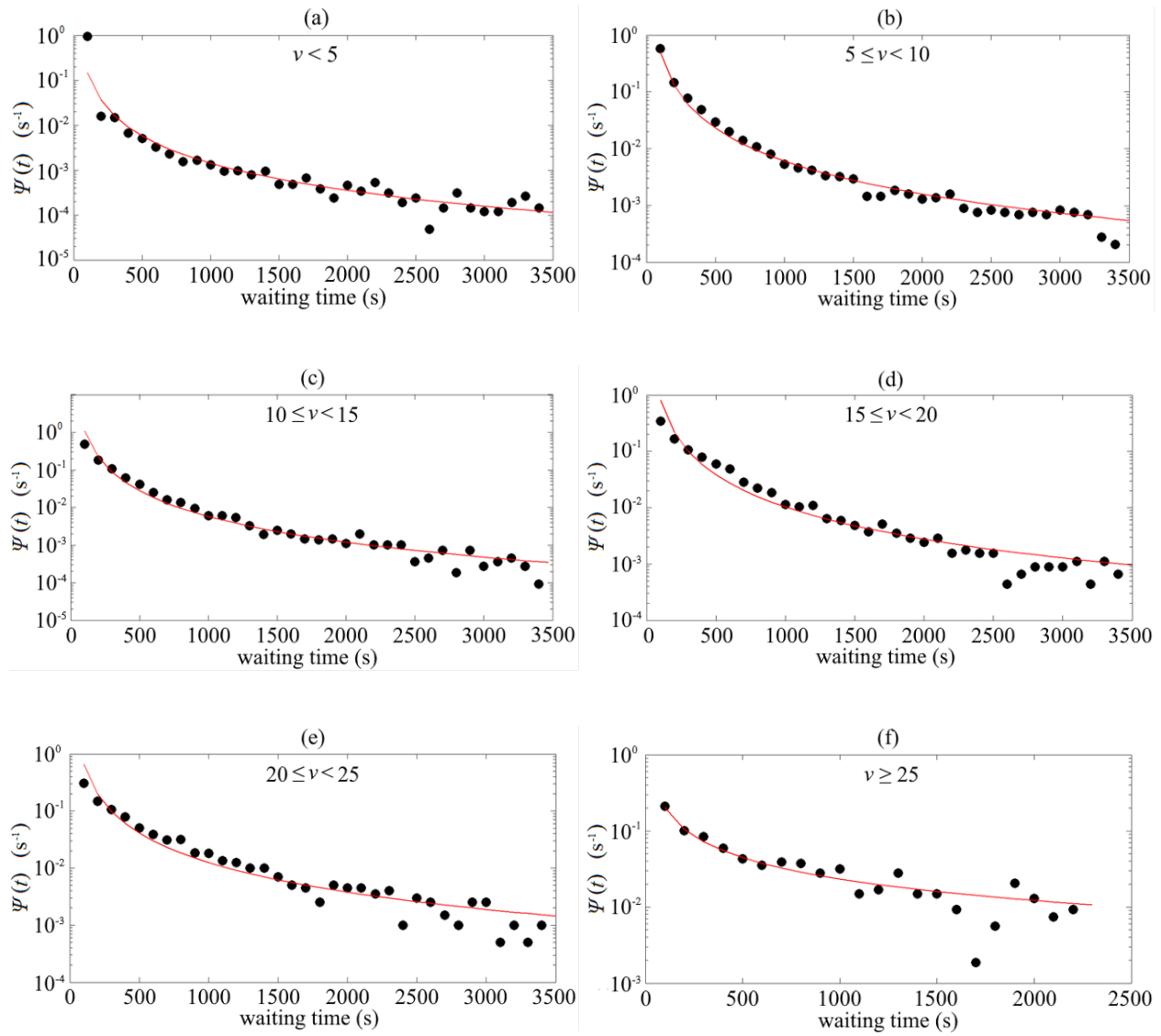


Fig. 3. Waiting time probability density for $\nu < 5$ (a), $5 \leq \nu < 10$ (b), $10 \leq \nu < 15$ (c), $15 \leq \nu < 20$ (d), $20 \leq \nu < 25$ (e), and $\nu \geq 25$ (f)

Table 1. Fitting parameters for the power law (see equation (2))

	C	α	R^2
(a)	1.5×10^3	2.0	0.940
(b)	3.6×10^3	1.9	0.999
(c)	3.7×10^4	2.3	0.954
(d)	5.0×10^3	1.9	0.910
(e)	1.8×10^3	1.7	0.904
(f)	1.5×10^1	0.94	0.577

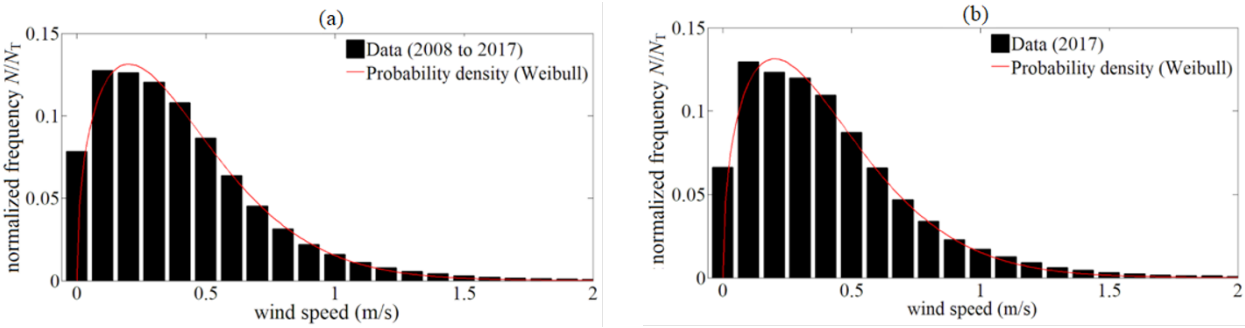


Fig. 4. Histogram of wind speed for (a) the 2008–2017 period at Takayama: $W(v)$ (solid line) fitted with $A = 0.08$, $c = 0.45$, and $k = 1.45$ ($R^2 = 0.86$), and for (b) January–December 2017: $W(v)$ (solid line) fitted with $A = 0.08$, $c = 0.45$, and $k = 1.45$ ($R^2 = 0.89$)

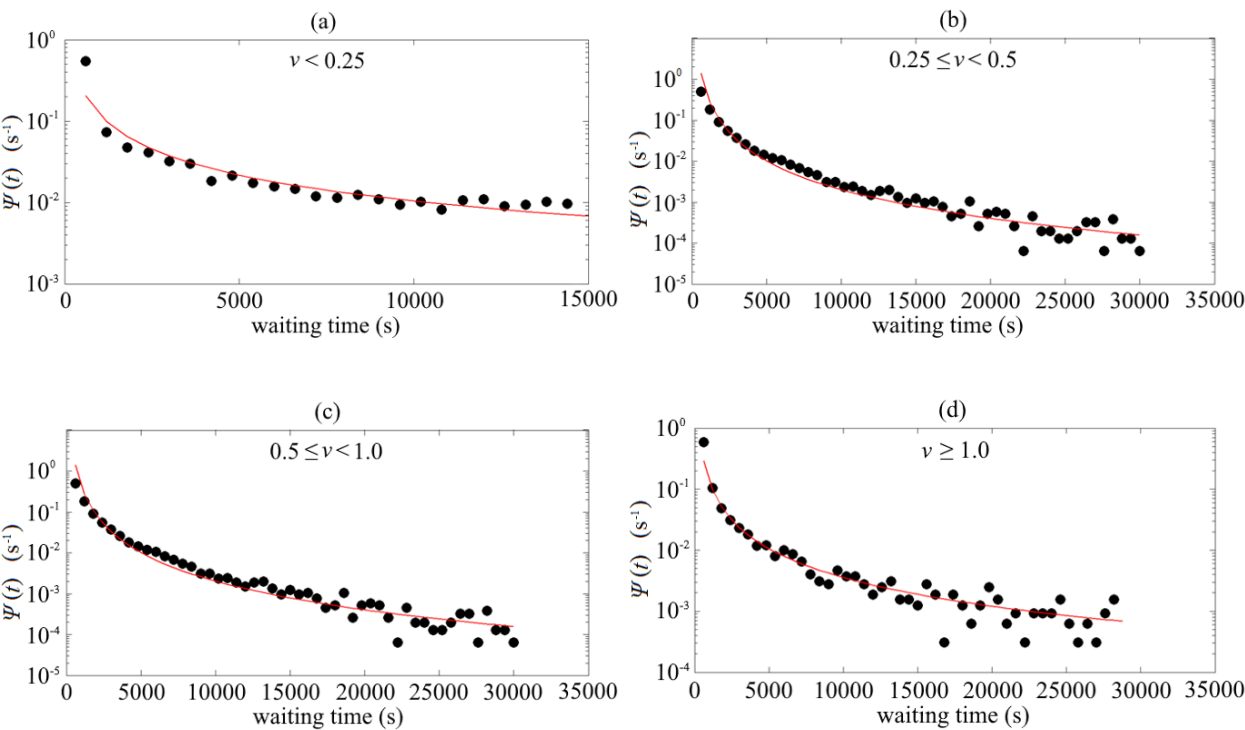


Fig. 5. Waiting time probability density for $v < 0.25$ (a), $0.25 \leq v < 0.5$ (b), $0.5 \leq v < 1.0$ (c), $v \geq 1.0$ (d)

Table 2. Fitting parameters for the power law (see equation (2))

	C	α	R^2
(a)	1.8×10^2	1.1	0.863
(b)	4.0×10^6	2.3	0.961
(c)	4.7×10^4	1.8	0.998
(d)	6.4×10^3	1.6	0.953

Discussion

The previous section showed that the histogram of the wind speed variation over a given period is described by the Weibull-type probabilistic distribution $W(v)$ (see Fig. 2 and 4). It was also shown that the waiting-time distribution $\Psi(t)$ for producing a wind speed v follows a power law (equation (2)).

In the present section, we first discuss the origin of $W(v)$ used in the wind speed v (equation (1)). An easier approach may be a generalization of the Rayleigh distribution (RD), i. e., the case $k = 2$ in equation (1) (Hofmann, Okafor 2001; Muller et al. 2002), where the RD is regarded as a special case of the Weibull distribution. Note that the RD was originally applied to propagating electromagnetic waves with random reflection and scattering (a two-dimensional random vector), although wind (or sound) waves are completely different from electromagnetic waves. In the RD, the magnitude of the signal intensity A is given by

$$P_{RD}(A) = 1 - \exp\left[-\left(\frac{A}{c}\right)^2\right], \quad (3)$$

where the variable A is used for the RD, but not velocity v . The probability density, $dP_{RD}(A)/dA$, is then given by

$$dP_{RD}(A)/dA = \frac{2}{c}\left(\frac{A}{c}\right) \exp\left[-\left(\frac{A}{c}\right)^2\right]. \quad (4)$$

Note that equation (4) is equivalent to equation (1) with $k = 2$. The exponent k , when smaller than 2, can be predicted from the concept of fractional dynamics. A vector representation in fractional space can be introduced: e. g., $x^2 + y^2 = r^2$ is transferred into $x^\alpha + y^\beta = r^\gamma$ (non-integer $\alpha, \beta, \gamma < 2$). Consequently, $k = 2$ in Euclid space can be modified to $k < 2$ in non-Euclid space (Vicsek 1989).

Next, we will discuss the waiting-time distribution $\Psi(t)$. We begin with the well-known Poisson waiting time distribution in the time domain given as (Papoulis 1965)

$$\Psi(t) = \lambda \exp(-\lambda t), \quad (5)$$

where λ is a constant with dimension s^{-1} . We further assume that wind can be generated by a pressure (potential) difference between two blocked random sites (i. e., a potential barrier U), as shown in Fig. 6. The parameter λ can be determined by a potential energy barrier U and is given by

$$\lambda = \lambda_0 e^{-\frac{U}{U_0}}, \quad (6)$$

where λ_0 and U_0 are constants.

In complex processes, such as wind scattering, the potential U may have distribution, e. g.,

$$P(U) = \frac{1}{U_m} e^{-\frac{U}{U_m}}, \quad (7)$$

where U_m is a constant. Then, λ is distributed in some manner $G(\lambda)$ given by (Papoulis 1965)

$$G(\lambda) = \frac{P(U)}{\left|\frac{d\lambda}{dU}\right|} = \frac{U_0}{\lambda} \frac{1}{U_m} e^{-\frac{U}{U_m}} = \frac{U_0}{\lambda} \frac{1}{U_m} e^{\frac{U_0 \ln(\lambda/\lambda_0)}{U_m}} = \frac{k}{\lambda} \left(\frac{\lambda}{\lambda_0}\right)^k \propto \lambda^{k-1}, \quad (8)$$

where $k = U_0/U_m$. Equation (5) is then modified to

$$\Psi(t) = \int G(\lambda) \lambda \exp(-\lambda t) d\lambda = C \int \lambda^k e^{-\lambda t} d\lambda = C t^{-1-k} = C t^{-\alpha}, \quad (9)$$

where C is a constant and $\alpha = 1 + k$, replicating well the experimental data (see Fig. 3 and 5). The parameter k may depend on the wind speed v , since complexities such as wind scattering etc. should be different for v .

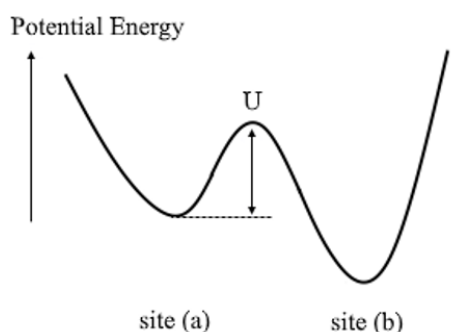


Fig. 6. Potential barrier U between two sites (a) and (b)

Conclusions

Time variations in wind speed at different locations, near the seaside in East Timor and on the mountain side in Japan, were analyzed using a statistical approach in the time domain. The WS histograms at these locations were well approximated by the Weibull distribution. The reason for following the Weibull distribution was discussed in terms of the generalization of the Rayleigh distribution. The waiting time probability density for WS, defined as the time during which the wind speed remains below or above a given threshold value, was found to follow a power law scaling with time, $t^{-\alpha}$ ($\alpha < 2.5$). This behavior may be associated with long-term correlations and is not consistent with a Poisson-type distribution. It was found that the characteristic features of $W(v)$ and $\Psi(t)$ were almost the same even at completely different locations on our globe.

Conflict of Interest

The authors declare that there is no conflict of interest, either existing or potential.

Author Contributions

All authors made an equivalent contribution to the preparation of the publication.

Acknowledgement

The authors would like to thank Prof. T. Kobayashi for providing the wind speed data obtained at the Takayama Field Station of the River Basin Research Center, Gifu University. We also thank the Japan International Cooperation Agency (JICA) for supporting our activities at UNTL.

References

- Apt, J. (2007) The spectrum of power from wind turbines. *Journal of Power Sources*, 169 (2), 369–374. <https://doi.org/10.1016/j.jpowsour.2007.02.077> (In English)
- Belo, A. F., Shimakawa, K. (2021) Statistical and spectral analysis of wind power: Fractional oscillation dynamics. *Physics of Complex Systems*, 2 (4), 141–148. <https://www.doi.org/10.33910/2687-153X-2021-2-4-141-148> (In English)
- Bucaneg, D., Wan, Y. (2002) Short-term power fluctuations of large wind power plant. *Journal of Solar Energy Engineering*, 124 (4), 427–431. <https://doi.org/10.1115/1.1507762> (In English)
- Hasche, B. (2010) General statistics of geographically dispersed wind power. *Wind Energy*, 13 (8), 773–784. <https://doi.org/10.1002/we.397> (In English)
- Hofmann, W., Okafor, F. N. (2001) Doubly-fed full-controlled induction wind generator for optimal power utilisation. In: *4th IEEE International Conference on Power Electronics and Drive Systems. IEEE PEDS 2001*. [S. l.]: IEEE Publ. [Online]. Available at: <https://doi.org/10.1109/PEDS.2001.975339> (accessed 10.05.2026). (In English)
- Joselin, H. G. M., Iniyamb, S., Sreevalsanic, E., Rajapandiand, S. (2007) A review of wind energy technologies. *Renewable and Sustainable Energy Reviews*, 11 (6), 1117–1145. <https://doi.org/10.1016/j.rser.2005.08.004> (In English)
- Liu, J., Ren, G., Wan, J., Guo, Y., Yu, D. (2016) Variogram time-series analysis of wind speed. *Renewable Energy*, 99, 483–491. <https://doi.org/https://doi.org/10.1016/j.renene.2016.07.013> (In English)

- Matsfelt, J., Davidson, L. (2021) Large eddy simulation: A study of clearings in forest and their effect on wind turbines. *Wind Energy*, 24 (12), 1388–1406. [Online]. <https://doi.org/10.1002/we.2637> (accepted 28.08.2021). (In English)
- Muller, S., Deicke, M., De Doncker, R. W. (2002) Doubly fed induction generator systems for wind turbines: A viable alternative to adjust speed over a wide range at minimal cost. *IEEE Industry Applications Magazine*, 8 (3), 26–33. <https://doi.org/10.1109/2943.999610> (In English)
- Murthy, K. S. R., Rahi, O. P. (2014) Estimation of Weibull parameters using graphical method for wind energy applications. In: *18th National power systems conference (NPSC–2014)*. [S. l.]: IEEE Publ. [Online]. Available at: <https://www.doi.org/10.1109/NPSC.2014.7103858> (accepted 28.08.2021). (In English)
- Papoulis, A. (1965) *Probability, random variables, and stochastic processes*. New York: McGraw-Hill, 266 p. (In English)
- Vicsek, T. (1989) *Fractal growth phenomena*. Singapore: World Scientific Publ., 384 p. (In English)