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Original Article

Optimal Probability Distribution Models for Wind Speed Prediction: Strategies to Advance Wind Energy Development in Vietnam

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Abstract - *This paper aims to provide data and propose viable strategies for effectively harnessing wind energy by introducing probabilistic models for wind speed prediction. The objective is to improve the accuracy of wind speed forecasts, thereby mitigating risks for stakeholders and building investor confidence in the development of wind energy. This aligns with the Vietnamese government's strategy to reduce greenhouse gas emissions, aiming to achieve 23,896 MW of wind power capacity by 2030, including 75% onshore and 25% offshore wind power. Wind speed data measured in a locality in Vietnam from 2017 to 2022 were evaluated using fitting methods and goodness of fit methods to determine the most appropriate probability distribution model. Findings indicate that the Gamma model best fits this locality under short-term, medium-term, and long-term forecasting scenarios. However, it is suggested that the Normal distribution model should be slightly prioritized in medium-term and long-term scenarios, whereas the Generalized Extreme Value model is found to be the least suitable.*

Keywords - *Wind energy, Wind speed forecast, Probability distribution, Energy development strategy, Renewable.*

1. Introduction

1.1. Literature Review

The increasing global focus on renewable energy sources like wind power is driven by the need to reduce greenhouse gas emissions and achieve sustainable development [1]. While wind power presents a promising solution, the inherent uncertainty in energy production due to fluctuating wind speeds poses significant challenges for stakeholders in the energy market [2]. This uncertainty can impact technical and economic aspects, including potential compensation to electricity buyers during energy shortages [3]. Previous studies have significantly focused on employing probability distribution models to reduce uncertainties in wind speed forecasting and optimize wind energy utilization. For instance, the Weibull distribution has been widely applied to assess wind energy uncertainties in the integration of wind and thermal energy systems, as well as to analyze wind speed patterns in Bangladesh [4]. Additionally, the Generalized Extreme Value (Ev) model has been utilized to calibrate aggregated wind speed forecasts in weather prediction [5]. Global wind energy development strategies, such as the European Union's clean energy transition [6] and South Asia's renewable energy development plan [7], have highlighted the critical role of selecting appropriate distribution models in managing wind energy uncertainties.

1.2. Motivations and Contributions

In Vietnam, which has pledged to achieve net-zero emissions by 2050 [8], and in neighboring regions, research on wind speed probability distribution models tailored to the local context remains scarce. While some survey data are available from areas with substantial wind potential, a comprehensive assessment of the suitability of these distribution models for the region's unique climatic conditions and wind characteristics is still lacking. This gap has led to an insufficient scientific foundation to guide investors and policymakers in advancing sustainable wind energy development.

1.3. Key Contributions of the Study Include

1.3.1. Identifying Optimal Probability Distribution Models

This study employs rigorous evaluation techniques such as Maximum Likelihood Estimation (ML), R-Square (R^2), Root Mean Square Error (RMSE), Chi-Square (X^2), and Kolmogorov–Smirnov (KS) tests [9], to determine the most suitable probability distribution models for measured wind speed data in Vietnam.

1.3.2. Supporting Wind Energy Development Strategies

The study provides detailed data and analyses to support policy formulation and the implementation of wind energy development strategies in Vietnam up to 2030, with a long-term vision extending to 2050. Additionally, it contributes to promoting investments in wind energy that are aligned with global sustainable development goals.

1.3.3. Enhancing Forecast Accuracy

The research proposes solutions to improve the accuracy of wind speed forecasts, minimize uncertainties in energy production, and optimize the economic efficiency of wind energy projects in Vietnam. These findings are valuable for Vietnam and have broad applicability to similar geographical regions in Southeast Asia that face comparable challenges in wind power development. The study contributes to reducing wind speed forecasting errors in the region by leveraging the wind speed data provided in this research.

2. Methodology of Wind Speed Probability Distribution Assessment

The paper focuses on evaluating and selecting appropriate probability distribution models for the surveyed area to improve wind speed forecasting accuracy and assess uncertainty levels, as discussed in [10]. Based on the forecasting time horizon, predictions can be categorized into four types: very short-term, short-term, medium-term, and long-term [11]. Regarding probability distribution models, the literature in [12] describes their wide range of applications across various fields, with commonly used models including Gamma (Gm) and Ev. Notably, [13] emphasizes that the Weibull (Wb) model is one of the most widely used models in the energy sector. Therefore, this study proposes to evaluate the Wb, Gm, and Ev distribution models in addition to the Normal (Nm) distribution model.

2.1. Probability Distribution Models

2.1.1. Weibull Distribution

The Probability Distribution Function (PDF) of the Wb model is described by the following expression [14]:

$$f(x) = \begin{cases} \frac{c}{\sigma}\left(\frac{x}{\sigma}\right)^{(c-1)} e^{-\left(\frac{x}{\sigma}\right)^{c}} & x \geq 0 \\ 0, & x < 0, \end{cases} \quad (1)$$

Here, the indices σ và c describe the scale and shape of the distribution. The cumulative probability distribution is transformed into [13]:

$$F(x) = 1 - e^{-\left(\frac{x}{\sigma}\right)^{c}}, x \geq 0 \quad (2)$$

2.1.2. Gamma Distribution

$$f(x) = \begin{cases} \frac{1}{\sigma^{c}\Gamma(c)} x^{(c-1)} e^{-\left(\frac{x}{\sigma}\right)} & x \geq 0 \\ 0, & x < 0, \end{cases} \quad (3)$$

$$F(x) = \frac{1}{\sigma^{c}\Gamma(c)} \gamma\left(c, \frac{x}{\sigma}\right), x \geq 0 \quad (4)$$

The Gm distribution has recently merged in predicting wind speeds in various regions, such as India [15], showing a close relationship with normal and exponential distributions. The probability and cumulative distribution functions are described as follows [13]. The coefficients σ and c also have the same meaning as Wbl. Particularly Γ is called the gamma function and is calculated by (c-1)! [16].

2.1.3. Generalized Extreme Value Distribution

The Ev model is a continuous probability distribution comprising three extreme components: Frechet and Weibull. The probability distribution and cumulative distribution are described as follows [14, 13]:

$$f(x) = \begin{cases} \frac{1}{\sigma}\left[1 + c\left(\frac{x-\mu}{\sigma}\right)\right]^{-\left(1+\frac{1}{c}\right)} e^{-\left[1+c\left(\frac{x-\mu}{\sigma}\right)\right]^{-\left(\frac{1}{c}\right)}} & 1 + c\left(\frac{x-\mu}{\sigma}\right) \geq 0 \\ 0, & 1 + c\left(\frac{x-\mu}{\sigma}\right) < 0, \end{cases} \quad (5)$$

$$F(x) = e^{-\left[1+c\left(\frac{x-\mu}{\sigma}\right)\right]^{-\left(\frac{1}{c}\right)}}, 1 + c\left(\frac{x-\mu}{\sigma}\right) \geq 0 \quad (6)$$

The coefficients c, σ, μ are sharp, scale and local, respectively.

2.1.4. Normal Distribution

Nm is commonly used in many different fields for standard probability statistics. The PDF is represented as follows [17]:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\left(\frac{(x-\mu)^{2}}{2\sigma^{2}}\right)} \quad (7)$$

The coefficient μ represents the average value, while σ describes the normal distribution coefficient.

2.2. Fitting Methods and Goodness of Fit

Determining the most appropriate parameters of the probability distribution model is the initial step. Once the parameters are clearly defined, goodness of fit methods are applied to evaluate and select the most suitable probability distribution model for the dataset [14, 18].

2.2.1. Maximum Likelihood Fitting

ML is one of the widely used methods for fitting and estimating the parameters of wind speed distribution models [19]. First, the likelihood function or the logarithmic likelihood function is constructed, and then the parameter values are searched for to maximize this function. Iterative methods such as Newton's are employed to estimate the maximum likelihood efficiently in an asymptotic sense and to achieve minimal variance [20]. Additionally, some studies have applied an improved ML method, known as the alternative maximum likelihood method, for modeling wind speed distribution. This method is based on the idea of linearizing the nonlinear terms using a Taylor series and deriving parameter estimators in a non-iterative manner. Ultimately, the results of ML fitting establish the best parameters for the evaluated probability distribution model.

2.2.2. R-Square Evaluation

The R-squared represents the square of the correlation between the observed values and the predicted values. It is also referred to as the square of the multiple correlation coefficient and the multiple coefficient of determination. This metric measures the degree of success in explaining the variability of the measured data. It is commonly used to assess how well a nonlinear function fits a given statistical data set. The higher the value, the better the fit. The R-squared value is calculated as follows [20]:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - x_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (8)$$

Here, y and x are the corresponding statistical and functional values, $\bar{y}$ is the average functional value.

2.2.3. Root Mean Square Error

The RMSE quantifies the discrepancy between observed probabilities and those estimated by the probability function, indicating the model's goodness of fit. A lower RMSE value signifies a better fit. Due to its sensitivity to outliers, RMSE is often used in conjunction with the square index. The calculated value is [20],

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}\left(F_i - \hat{F}_i\right)^2\right]^{\frac{1}{2}} \quad (9)$$

F and $\hat{F}$ represent probability functions and observed values.

2.2.4. Chi-Square Evaluation

The chi-square statistic, based on the frequency of occurrences, is commonly used to assess the accuracy of probability distribution functions. Therefore, this statistic indicates whether the chosen distribution function is valid when evaluated against a critical value. The statistic is calculated as follows [14]:

$$X^2 = \sum_{i=1}^{N}\frac{(O_i - E_i)^2}{E_i} \quad (10)$$

In this context, Oi represents the number of observations estimated using each distribution's estimated probability density function. Ei denotes the expected number of observations, calculated through a frequency histogram based on the measured data.

2.2.5. Kolmogorov–Smirnov Evaluation

The Kolmogorov-Smirnov statistic assesses the maximum difference between the cumulative distribution function of a model and the empirical distribution function. When the measured value increases or decreases too abruptly in comparison to the distribution function, it indicates that the chosen distribution may be inappropriate. The statistic is calculated using the following expression [14]:

$$KS = max(|F_1(x) - F_2(x)|) \quad (11)$$

Where F1(x) is the cumulative probability measured compared with the theoretical probability, F2(x).

3. Data

3.1. Wind Power Development Strategy of Vietnam by 2030

3.1.1. Review of Wind Power Development Strategy

Table 1. Wind power planning data by 2030 [21]

Regions	Planning by 2030 (MW)		
	Total	Onshore	Offshore
Northern	8,264	5,764	2,500
Middle	4,791	4,291	500
Southern	10,841	7,841	3,000
Total	23,896	17,896	6,000

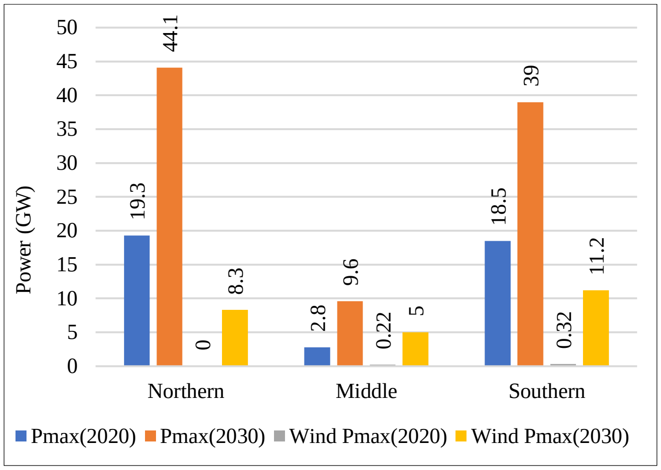

Fig. 1 Electricity load and wind power by 2030 [8, 22]

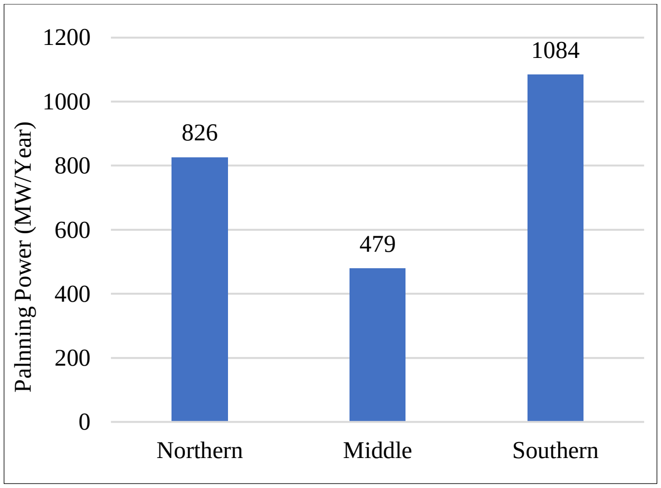

Fig. 2 Annual average increase in wind power [21]

Table 2. Installed wind power capacity of countries

Countries		Potential (MW)	Year	Installed Capacity (MW)
Afghanistan	[7]	66.726	2019	0
Bangladesh		20.000	2019	3
Bhutan		63.895	2019	1
India		102.778	2020	32878
Maldives		288	2019	1
Nepal		3.000	2019	0
Pakistan		346.000	2020	792
Sri Lanka		24.000	2019	146
Vietnam		821.173	2022	3986

According to the forecast in [8], electricity demand is expected to reach a peak load of over 92,000 MW by 2030, while total power capacity expansion is projected to be around 138,000 MW. Wind power is expanding rapidly, with a planned increase of nearly 24,000 MW, as outlined in Table 1, reflecting an annual growth rate of approximately 28%. The southern region is leading this growth, with an annual increase of 21%, while the middle region shows the slowest growth at 9%, as indicated in Figure 1. The northern region is growing at about 16% annually, with average annual capacity increases of 826 MW in the north, 479 MW in the middle region, and 1,084 MW in the south, as shown in Figure 2. By 2030, wind power capacity is projected to exceed 10,000 MW, largely based on detailed plans for onshore wind projects. Currently, 58% of the remaining capacity is in the planning phase and open to investors. This capacity is evenly divided between onshore and offshore wind power, with approximately 7,800 MW allocated to onshore and 6,000 MW to offshore. According to the wind power development plan in [21], wind energy is expected to make up more than 13% of Vietnam's total energy capacity by 2030, with an estimated 28,000 MW. However, this only taps into about 13% of the country's full wind energy potential. As reported in [8], Vietnam has over 200,000 MW of onshore wind capacity and around 600,000 MW offshore.

3.1.2. Comparison of Asian Countries

According to reference [21], Vietnam is among the countries with a robust wind energy investment and development strategy, driven by strong initial government support policies and a substantial, favorable wind energy resource base, as shown in Table 2.

3.2. Wind Speed Data

The wind speed data was collected from a midland region in the south-central coast of Vietnam, an area with a significant future wind energy development strategy [8]. Wind speeds were measured at a height of 10 meters above ground level. The data was recorded at 10-minute intervals, encompassing maximum speed, minimum speed, average speed, and standard deviation. The dataset utilized for the research spans six years, from 2017 to 2022. Three simulations of the dataset were conducted: (i) short-term, the data was divided into hourly sample subsets for each day; (ii) medium-term, the data was segmented into daily sample subsets for each month; and (iii) long-term, the data was organized into monthly sample subsets for each year. Figure 3 illustrates the measured data over a span of six years. While not immediately evident, it is observed that the pattern remains largely consistent across four seasons within each year: (1) Season 1: from December of the preceding year to February. (2) Season 2: from March to May. (3) Season 3: from June to August. (4) Season 4: from September to November. Seasons 1 and 3 exhibit higher wind speeds than Seasons 2 and 4.

4. Experimental Results and Discussion

4.1. Comparison of Models

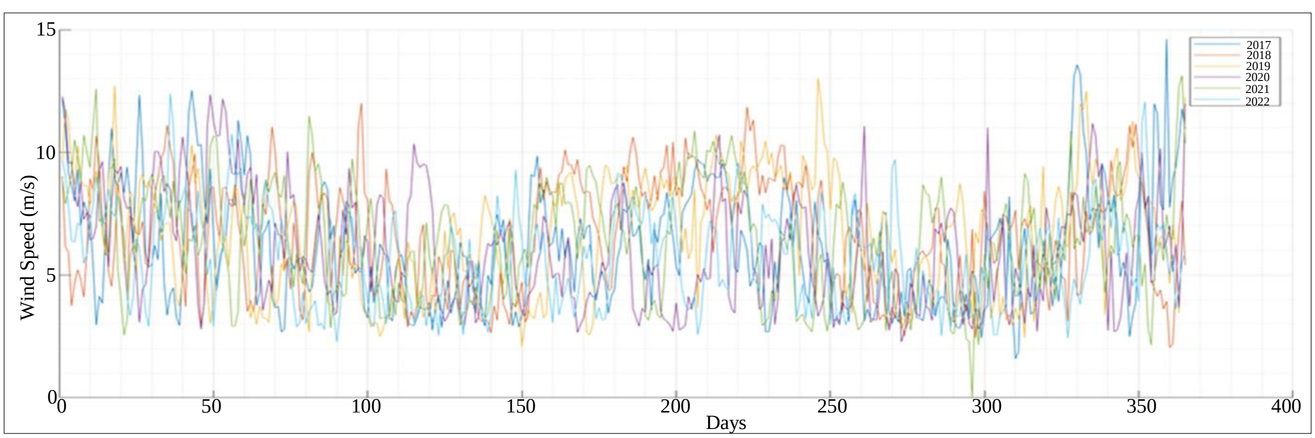

Fig. 3 Wind velocity data measured

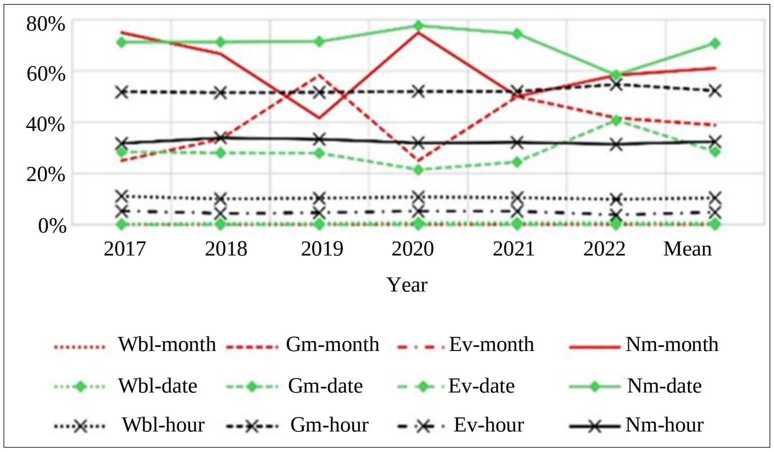

Fig. 4 Dominance ratio of distribution models

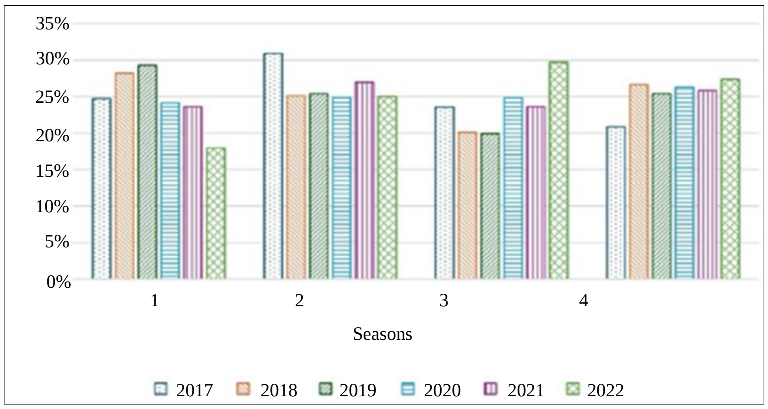

Fig. 5 Dominant dates of Nm distribution

The survey results of four distribution types with three illustrated cases are presented in Figure 4. The curves depict a relatively stable trend in the selection count over the years. However, the case for months exhibits variability, particularly between the Nm and Ev distributions. The highest selection rate occurs with the Nm distribution in the daily case, averaging around 70%. Conversely, the lowest is observed with the Wb distribution in both monthly and daily cases. Upon closer examination of each case, Gm holds the highest selection proportion for short-term hourly predictions, followed by Nm, Wb, and Ev, which is the least preferred. For medium and long-term cases, the Nm distribution predominates, especially in the medium-term, followed by Gm. Wb and Ev's distributions are scarcely chosen in these scenarios. Hence, for short-term predictions, the Gm distribution appears most suitable, although other distributions should also be considered, albeit with lesser suitability. Conversely, for medium and long-term predictions, the Nm distribution seems more appropriate. Wb and Ev distributions are discouraged for use in these contexts.

4.2. Medium-Term Case

Figure 5 presents the results of the proportion of Nm selection distribution across seasons over the years. Cases suggest a seemingly equivalent outcome across all four seasons. However, some anomalous fluctuations are believed to be weather-related. For instance, in the second season of 2017, the prevalence of storms compared to other years led to a notably higher proportion of Nm selection distribution [23, 24]. Conversely, in the first season of 2022, the presence of tropical low-pressure systems and weaker cold air mass compared to previous years resulted in a significantly lower proportion [25]. Thus, a medium-term case based on Nm distribution is recommended but remains contingent upon weather conditions.

4.3. Short-Term Case

Figures 6 and 7 further confirm the superiority of the Gm distribution in the hourly and annual analysis. While alternative distributions are viable, Gm and Nm stand out as the more dominant, with significantly higher selection probabilities of 0.55 and 0.31, respectively. In contrast, Wb shows a lower probability of 0.10, and Ev has the lowest at just 0.04. Between the hours of 12:00 to 15:00, there appears to be a balance between these two distribution models. Perhaps the high and stable wind velocities mitigate the influence of distribution types. The Wb distribution warrants consideration due to its stability, whereas Ev exhibits a lower preference ratio. A comparison across months in 2022 in Figure 8 illustrates relatively stable preference ratios for the models. However, the

Nm distribution experienced a sharp decline in February, attributed to abrupt decreases in tropical pressure rates and cold air in that month of 2022. In the case of seasons, the Gm distribution seems less volatile, while the others fluctuate across Seasons 2 and 3, as depicted in Figure 9, corresponding to seasons characterized by high wind speed fluctuations due to weather fluctuations.

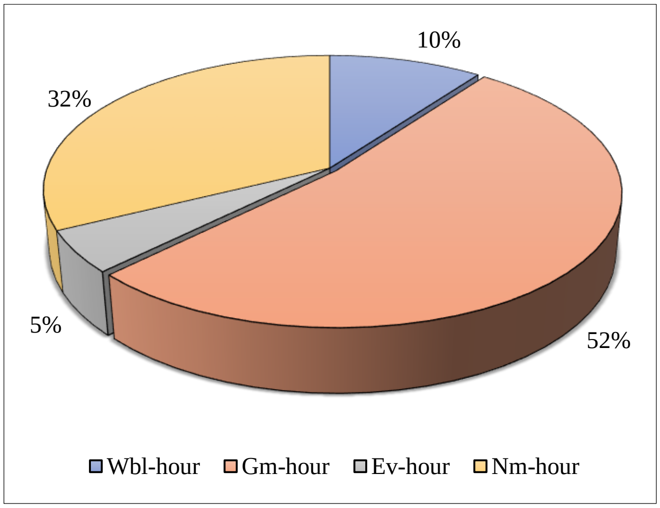

Fig. 6 Mean dominant in six years

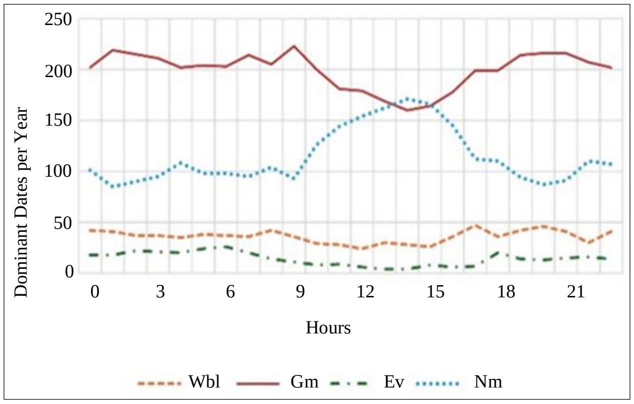

Fig. 7 Dominant dates in short-term simulation by 2022

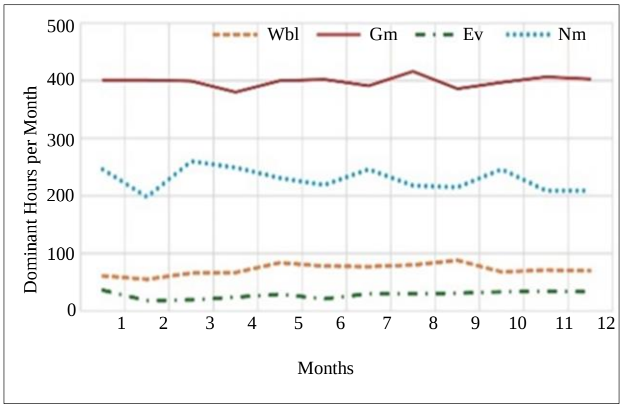

Fig. 8 Dominant in months by 2022

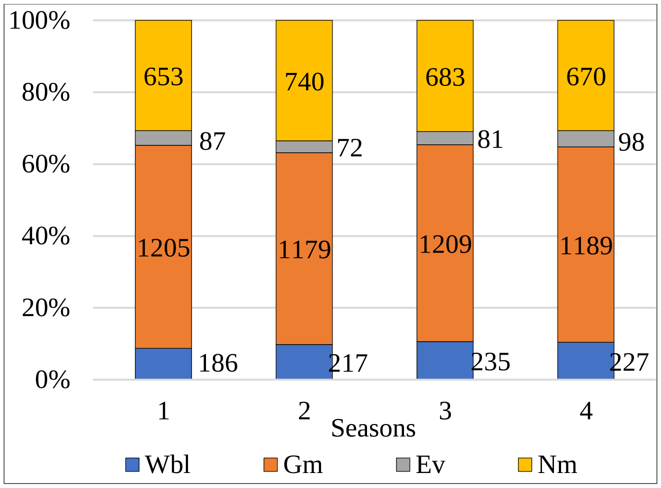

Fig. 9 Dominant in seasons by 2022

4.4. Comparison of Countries

Table 1. Survey of wind speed probability distribution models of countries

Countries	Ref.	Year of Survey	Proposed Model
Turkey	[12]	2013	Extreme Value
Trinidad and Tobago	[14]	2000-2015	Rayleigh
Iran	[13]	2008-2010	Gamma
Vietnam	This article	2017-2022	Gamma

Although various studies have applied the Weibull probability distribution to assess error deviations in wind speed predictions for optimization problems in wind energy, survey data from several countries suggest that other distribution models may provide greater accuracy, as summarized in Table 3. For instance, Turkey recommends the Extreme Value model, Trinidad and Tobago proposes the Rayleigh model, Iran suggests the Gamma model, and, in line with Iran's findings, Vietnam is also recommended to use the Gamma model, as supported by the results of this study.

5. Conclusion

The findings of this research, based on the analysis and evaluation of wind speed data, are designed to enhance the strategy for wind energy development in alignment with Vietnam's power planning objectives. The study demonstrates that the Gm probability distribution is the most effective for predicting hourly short-term wind power generation. In some cases, the Nm distribution may serve as a viable alternative or complement to Gm. Importantly, these results diverge from those presented in reference [12], where the Ev distribution provided superior overall model performance. The Wb distribution, often utilized in some prior scientific studies, should also be considered but appears to be less suitable, a sentiment aligned with the assertion in reference [14]. For medium-term, daily-based forecasting, it is advisable to prioritize the selection of the Nm distribution for evaluation over others. Conversely, a combination of both Nm and Gm distributions is recommended for long-term projections based on experimental findings. On the horizon axis, the process of selecting distributions appears to be less contingent upon seasons or months within the year. However, when examined by hourly intervals, the time frame between 12:00 and 15:00 shows minimal differentiation between the distributions Gm and Nm. Beyond this timeframe, the evaluation outcomes favor the proposed Gm distribution model. Despite the clear achievements highlighted by the research results, certain limitations remain, particularly regarding unusual weather patterns. The evaluation identified several unexpected storms, such as those in the second season of 2017 and the early season of 2022, in Figure 5, which could disrupt predictions. Correspondingly, for such anomalies, the Nm probability distribution is suitable across various localities, aligning with findings from previous studies.

Conflicts of Interest

The authors affirm the absence of relevant financial or non-financial conflicts of interest. Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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