Assessment of Power Curve Fitting Performance of Parametric Models for Wind Turbines

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Abstract-In wind energy systems, wind speed variability and wind power fluctuation negatively affect the power system reliability. To overcome this challenge, actual wind turbine power curves serve as one of the important tools for condition monitoring and troubleshooting, easier forecast of wind power production and ensuring the stable operation of wind turbines. Motivated by this, this study compares the goodness-of-fit results of polynomial, Fourier, Gaussian and sum of sines parametric models in wind turbine power curve fitting. According to the accuracy results obtained, 9th-degree polynomial, 8-term Fourier, 4-term Gaussian and 5-term sum of sines models show good parametric modeling performance in their own curve fitting category. Among them, 8-term Fourier model stands out by achieving the least power curve fitting errors. In addition, traditional benchmark models have been outdone in terms of the goodness-of-fit statistics.

Keywords: Wind turbine, power curve, parametric modeling, goodness-of-fit, comparison.

1. Introduction

Wind energy industry continues to grow and stands out as an important actor among renewable energies [1, 2]. In recent years, a large number of wind turbines have been installed in wind power plants around the world, and their operating and maintenance costs have also been high [3-5]. To monitor the performance of wind turbines and improve the utilization of wind energy, it is needed to generate precise practical power curves from average wind speeds and corresponding power outputs [6-8]. To address this, many research studies on the parametric modeling of wind turbine power curves have been conducted in the literature.

An explicit analytical equation was utilized for the generalization of different power curves [9]. A maximum likelihood-based Weibull distribution function was built for power curve assessment [10]. Least squares-based Weibull and linear distribution functions were applied for power curve monitoring [11]. Cubic, quadratic and linear power curves were improved using Weibull distribution function [12]. Approximate cubic, cubic, quadratic and exponential power curves were constructed for the region above the cut-in speed and below the nominal speed [13]. An interpolation formula based on a set of linear equations was also employed for the similar region in the power curve [14]. An optimized power curve was created to improve the efficiency issues in the low-wind-speed areas [15].

QR decomposition and least squares methods were used to calculate the design coefficients of 8th-degree polynomial power curve [16]. Piecewise functions were fitted on the bins of the power curve with 6th-, 5th- and 4th-degree polynomials [17]. A piecewise polynomial function with the 3rd-degree was also employed for more plausible power curves [18]. Multivariate polynomial power curves were tested under wake-free and wake-affected conditions [19, 20]. A data-driven error correction-based logistic function was developed to reflect the trend of wind power [21]. Compared to Hill and Weibull functions, a 3-parameter logistic function was found to be more stable in power curve modeling [22]. A firefly algorithm-based 4-parameter logistic function was developed for power curve characterization [23]. 3- and 5-parameter logistic functions were recommended to model the power curves of various wind turbines [24].

Particle swarm optimization, genetic algorithm, evolutionary programming and differential evolution were used to obtain the design coefficients of 4- and 5-parameter logistic power curves [25]. Deterministic process-based 3- and 4-parameter logistic and simplified deterministic process-based 4-parameter logistic power curve models were analysed to reformulate the parameters of logistic functions [26]. Least squares-based 7th-degree polynomial and 4-parameter logistic functions were compared for a smoother power curve [27]. 9th- and 5th-degree polynomial, logistic and double exponential functions were compared in terms of power curve modeling performance [28]. Grey wolf optimizer and backtracking search algorithm were hybridized, and combined with a loss function based on the error characteristic to construct modified hyperbolic tangent and logistic power curves [29]. Additionally, many other applications for parametric functions are available in [30-37].

From this literature summary, it is clear that the selection of parametric model is very essential in wind turbine power curve modeling. In this regard, the main objective of this study is to make a comparative analysis on the parametric modeling performance of polynomial, Fourier, Gaussian and sum of sines curve fitting models. As a result of the detailed comparisons, many useful goodness-of-fit assessments have been carried out in terms of the coefficient of determination, root mean squared error and sum of squared errors.

2. Power Curve Fitting

In the power curve modeling performed in this study, the fitting coefficients of sum of sines (F_1), Gaussian (F_2), Fourier (F_3) and polynomial (F_4) parametric models are determined utilizing the least squares method. The mentioned parametric models are formulated as below [38-41]. In Equation (1), n, c, b and a are the number of terms, phase constant, frequency and amplitude, respectively. In Equation (2), n, c, b, and a represent the number of peaks, peak width, centroid and amplitude, respectively. In Equation (3), n, w and a_0 denote the number of terms, fundamental frequency and constant term, respectively. In Equation (4), n and $n+1$ indicate the polynomial degree and polynomial order, respectively. In these equations, x is normalized by mean 5.48 and standard deviation 2.373. The mentioned parametric models are implemented in the curve fitting toolbox of Matlab R2016a. The coefficient of determination (R^2), root mean squared error (RMSE) and sum of squared errors (SSE) are employed for assessing the curve fitting accuracy. In addition, the wind turbine power curve dataset utilized in this study was taken from [42]. It included actual measurements recorded at 10-min intervals for 1 year. After data cleaning, the final dataset resulted in 47274 data points for wind speed and wind power parameters.

$$F_1 = \sum_{i=1}^{n} a_i sin(b_i x + c_i)\,, 1 \le n \le 8 \quad (1)$$

$$F_2 = \sum_{i=1}^{n} a_i e^{[-((x-b_i)/c_i)^2]}\,, 1 \le n \le 8 \quad (2)$$

$$F_3 = a_0 + \sum_{i=1}^{n} a_i\, cos(iwx) + b_i sin(iwx)\,, 1 \le n \le 8 \quad (3)$$

$$F_4 = \sum_{i=1}^{n+1} p_i x^{n+1-i}\,, 1 \le n \le 9 \quad (4)$$

2.1. Polynomial Fitting Results

The accuracy results of polynomial curve fitting models are listed in Table 1. According to this table, 9th-degree polynomial model succeeds the most accurate power curve fitting with SSE of 1.0852×10^8, RMSE of 47.9181 kW and R^2 of 0.986727. 8th-degree polynomial model follows it with SSE of 1.0854×10^8, RMSE of 47.9203 kW and R^2 of 0.986725. In addition, it outdoes 7th-degree to 2nd-degree polynomial models in terms of accuracy results, respectively. Nevertheless, 1st-degree polynomial model produces the most erroneous power curve fitting with SSE of 1.4854×10^9, RMSE of 177.2619 kW and R^2 of 0.818332. The fitting coefficients of 9th-degree polynomial model are computed as p_1=-0.004121, p_2 =0.1452, p_3=-1.072, p_4=1.202, p_5=11.57, p_6=-31.47, p_7=-48.13, p_8=221.3, p_9=434.5 and p_{10}=208.2. The wind turbine power curve fitted by 9th-degree polynomial model is given in Fig. 1. It should be noted that 3rd-, 2nd- and 1st-degree polynomials are also called cubic, quadratic and linear regression models in benchmark tests.

Table 1. Accuracy results of polynomial curve fitting models

Parametric Models	Curve Fitting Accuracy		
	SSE	RMSE	R^2
1st-degree polynomial model	1.4854×10^9	177.2619	0.818332
2nd-degree polynomial model	4.3008×10^8	95.3845	0.947399
3rd-degree polynomial model	1.9541×10^8	64.2953	0.976100
4th-degree polynomial model	1.4754×10^8	55.8689	0.981955
5th-degree polynomial model	1.1296×10^8	48.8850	0.986185
6th-degree polynomial model	1.1242×10^8	48.7684	0.986251
7th-degree polynomial model	1.1092×10^8	48.4419	0.986435
8th-degree polynomial model	1.0854×10^8	47.9203	0.986725
9th-degree polynomial model	1.0852×10^8	47.9181	0.986727

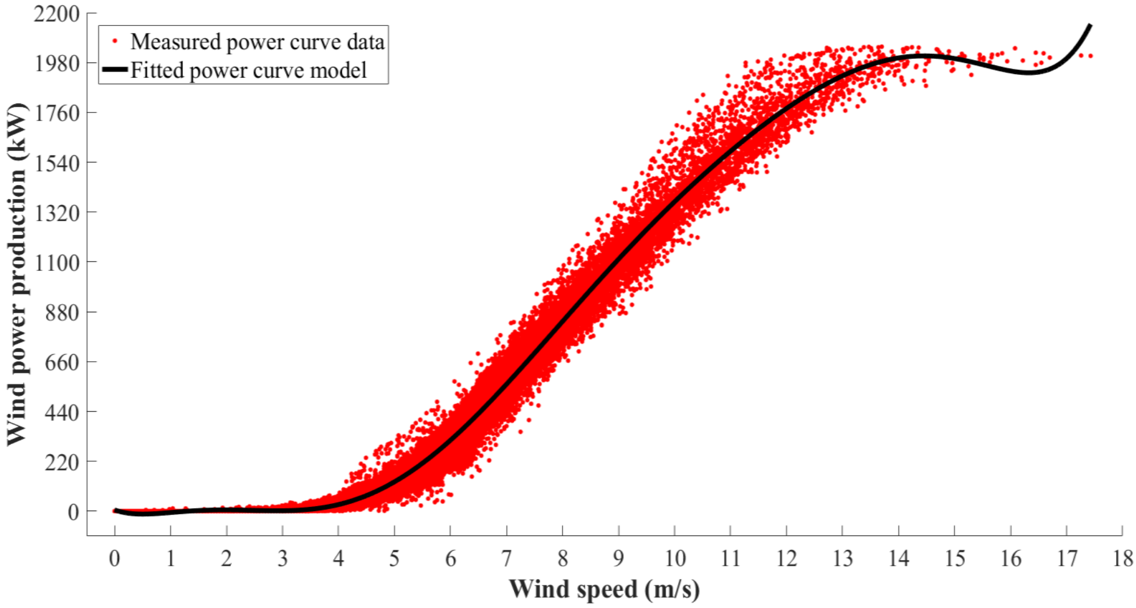

Fig. 1. The wind turbine power curve fitted by 9th-degree polynomial model.

2.2. Fourier Fitting Results

The accuracy results of Fourier curve fitting models are presented in Table 2. As observed from this table, 8-term Fourier model accomplishes the most correct power curve fitting with SSE of 1.0617×10^8, RMSE of 47.4001 kW and R^2 of 0.987014. It is pursued by 7-term Fourier model with SSE of 1.0624×10^8, RMSE of 47.4139 kW and R^2 of 0.987006. Moreover, on the basis of accuracy results, 6-term to 2-term Fourier models are surpassed, respectively. However, 1-term Fourier model results in the most inconsistent power curve fitting with SSE of 1.5932×10^8, RMSE of 58.0549 kW and R^2 of 0.980515. The fitting coefficients of 8-term Fourier model are found as a_0=940.2, a_1=-776.5, b_1=807.3, a_2=173.8, b_2=-66.7, a_3=-157.4, b_3=-80.95, a_4=28.62, b_4=108, a_5=16.57, b_5=-55.51, a_6=-32.34, b_6=16.24, a_7=12.38, b_7=3.45, a_8=-3.575, b_8=-8.332 and w=0.6445. The wind turbine power curve fitted by 8-term Fourier model is illustrated in Fig. 2.

2.3. Gaussian Fitting Results

The accuracy results of Gaussian curve fitting models are summarized in Table 3. Based on this table, 4-term Gaussian model achieves the best power curve fitting with SSE of 1.0625×10^8, RMSE of 47.4144 kW and R^2 of 0.987005. 6-term Gaussian model follows it with SSE of 1.0651×10^8, RMSE of 47.4743 kW and R^2 of 0.986974. In addition, it outperforms 5-term, 3-term, 7-term, 2-term and 8-term Gaussian models in terms of accuracy results, respectively. On the other hand, 1-term Gaussian model brings about the worst power curve fitting with SSE of 2.1269×10^8, RMSE of 67.0780 kW and R^2 of 0.973986. The fitting coefficients of 4-term Gaussian model are calculated as a_1=1762, b_1=6.09, c_1=3.041, a_2=-118.9, b_2=-0.2436, c_2=1.187, a_3=1261, b_3=2.722, c_3=2.22, a_4=51.66, b_4=0.8176 and c_4=0.508. The wind turbine power curve fitted by 4-term Gaussian model is depicted in Fig. 3.

Table 2. Accuracy results of Fourier curve fitting models

Parametric Models	Curve Fitting Accuracy		
	SSE	RMSE	R^2
1-term Fourier model	1.5932×10^8	58.0549	0.980515
2-term Fourier model	1.2553×10^8	51.5340	0.984647
3-term Fourier model	1.0940×10^8	48.1102	0.986620
4-term Fourier model	1.0747×10^8	47.6854	0.986855
5-term Fourier model	1.0690×10^8	47.5594	0.986925
6-term Fourier model	1.0632×10^8	47.4313	0.986996
7-term Fourier model	1.0624×10^8	47.4139	0.987006
8-term Fourier model	1.0617×10^8	47.4001	0.987014

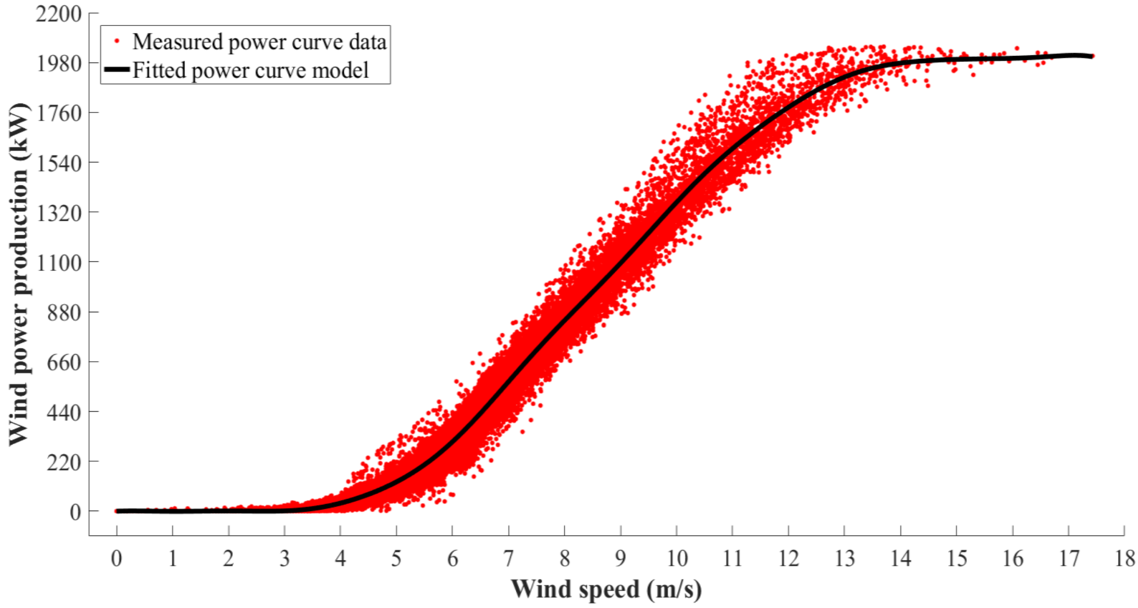

Fig. 2. The wind turbine power curve fitted by 8-term Fourier model.

Table 3. Accuracy results of Gaussian curve fitting models

Parametric Models	**Curve Fitting Accuracy**		
	SSE	**RMSE**	**R^2**
1-term Gaussian model	2.1269×10^8	67.0780	0.973986
2-term Gaussian model	1.0928×10^8	48.0820	0.986635
3-term Gaussian model	1.0673×10^8	47.5192	0.986947
4-term Gaussian model	1.0625×10^8	47.4144	0.987005
5-term Gaussian model	1.0671×10^8	47.5176	0.986949
6-term Gaussian model	1.0651×10^8	47.4743	0.986974
7-term Gaussian model	1.0699×10^8	47.5845	0.986914
8-term Gaussian model	1.1940×10^8	50.2689	0.985397

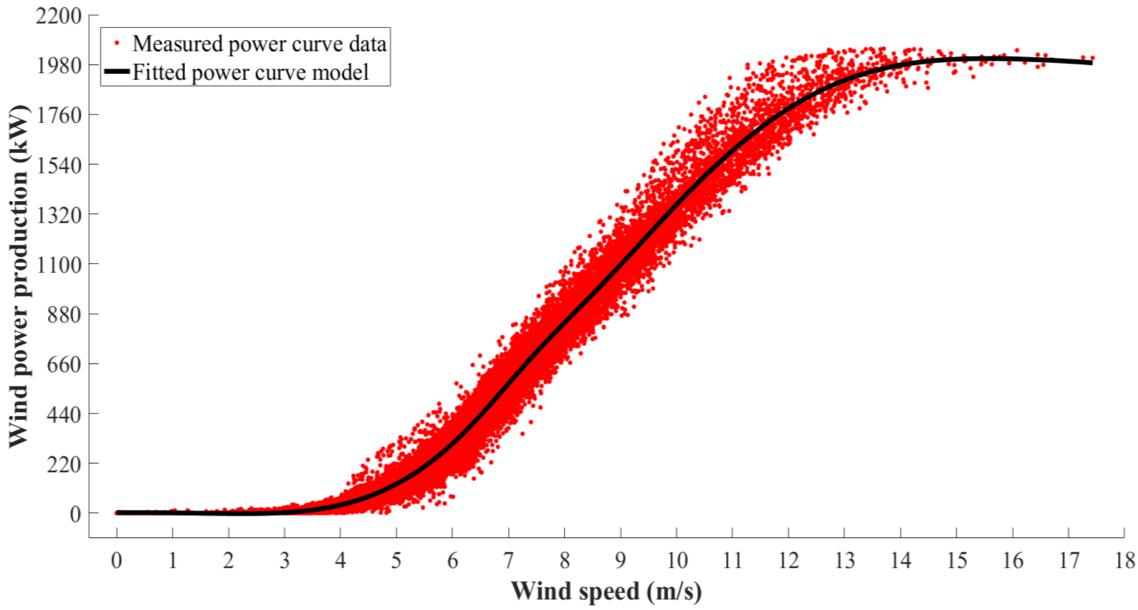

Fig. 3. The wind turbine power curve fitted by 4-term Gaussian model.

2.4. Sum of Sines Fitting Results

The accuracy results of sum of sines curve fitting models are provided in Table 4. As noticed from this table, 5-term sum of sines model realizes the smallest power curve fitting errors with SSE of 1.0679×10^8, RMSE of 47.5352 kW and R^2 of 0.986940. It is pursued by 6-term sum of sines model with SSE of 1.0680×10^8, RMSE of 47.5380 kW and R^2 of 0.986939. Moreover, on the basis of accuracy results, 4-term, 8-term, 7-term, 3-term and 2-term sum of sines models are surpassed, respectively. However, 1-term sum of sines model causes the biggest power curve fitting errors with SSE of 1.4855×10^9, RMSE of 177.2703 kW and R^2 of 0.818318. The fitting coefficients of 5-term sum of sines model are obtained as a_1=8131, b_1=0.3573, c_1=1.997, a_2=8198, b_2=0.4039, c_2=-1.055, a_3=63.99, b_3=1.841, c_3=-2.087, a_4=29.09, b_4=2.624, c_4=-0.2813, a_5=6.359, b_5= 4.814 and c_5=-2.449. The wind turbine power curve fitted by 5-term sum of sines model is shown in Fig. 4.

3. Conclusions

This paper introduces the detailed comparison of polynomial, Fourier, Gaussian and sum of sines models in terms of the coefficient of determination, root mean squared error and sum of squared errors for wind turbine power curve modeling. When considering the best power curve model in each curve fitting category, 8-term Fourier model provides lower SSE and RMSE values and higher R^2 value than 4-term Gaussian, 5-term sum of sines and 9th-degree polynomial models, respectively. On the other hand, when taking into account the worst power curve model in each curve fitting category, 1-term sum of sines model produces higher SSE and RMSE values and lower R^2 value than 1st-degree polynomial, 1-term Gaussian and 1-term Fourier models, respectively. Additionally, in case of making the comparison against traditional benchmark models, it is seen that 8-term Fourier model also performs better than logarithmic, exponential, cubic, quadratic and linear regression models. While the SSE, RMSE and R^2 values of

Table 4. Accuracy results of sum of sines curve fitting models

Parametric Models	Curve Fitting Accuracy		
	SSE	RMSE	R^2
1-term sum of sines model	1.4855×10^9	177.2703	0.818318
2-term sum of sines model	1.1482×10^8	49.2853	0.985957
3-term sum of sines model	1.0770×10^8	47.7347	0.986828
4-term sum of sines model	1.0681×10^8	47.5383	0.986937
5-term sum of sines model	1.0679×10^8	47.5352	0.986940
6-term sum of sines model	1.0680×10^8	47.5380	0.986939
7-term sum of sines model	1.0702×10^8	47.5899	0.986911
8-term sum of sines model	1.0701×10^8	47.5905	0.986912

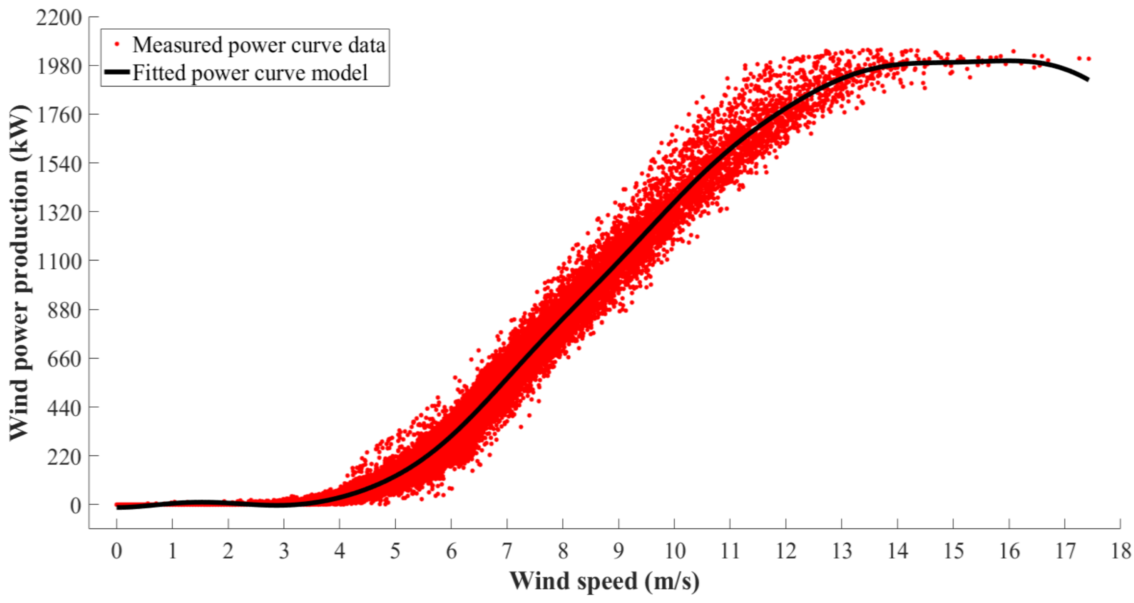

Fig. 4. The wind turbine power curve fitted by 5-term sum of sines model.

logarithmic regression model are computed as 4.6681×10^9, 316.5292 kW and 0.423240, respectively, the ones for exponential regression model are found as 1.5924×10^9, 183.5346 kW and 0.805247, respectively.

In future studies, for further analysis, the design coefficients of the most accurate power curve fitting models identified in this study can be approximated utilizing the recently-developed metaheuristic optimization algorithms in the literature.

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