Comparison of Outlier Detection Approaches for Wind Turbine Power Curves

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***Abstract*—Wind turbine power curves have great importance for power grid planning, wind energy assessment, and condition monitoring and troubleshooting of wind turbines. However, it is difficult to construct accurate wind turbine power curves due to the presence of outlier data points. This study compares the outlier detection approaches in the literature from different perspectives, i.e., wind farm/turbine location, rated wind power, data recording period, data recording interval and outlier identification performance. In consequence, many reasonable findings have been obtained and thus, several research directions have been indicated for wind turbine power curves.**

Keywords—Wind turbines, power curves, abnormality detection, data filtering, comparison

I. INTRODUCTION

Hydropower, solar energy, wind energy, bio-energy and geothermal energy are the primary renewable energy sources in the world [1]. The main purpose of using them is to reduce fossil fuel consumption and to provide a sustainable life [2, 3]. Unlike traditional energy sources, renewable ones are reliable and economic, and have not any negative impacts on the nature [4, 5]. In particular, wind energy has played a more important role in mitigating the energy crisis over the past decades [6]. The total global wind power capacity neared 743 GW in 2020 although it was 650 GW in 2019 [7].

In the growing wind industry, wind turbine power curves have great value in evaluating the operating state and performance of wind turbines [8]. According to Fig. 1, there are four main regions in a typical power curve of a pitch-regulated wind turbine [9, 10]. When v is less than v_{cut-in}, the output power is zero (Region 1). When v is greater than v_{cut-in} and less than v_{rated}, the output power increases rapidly (Region 2). When v is greater than v_{rated} and less than $v_{cut-off}$, the output power is constant (Region 3). When v is greater than $v_{cut-off}$, the wind turbine is shut down to prevent damage from high wind speeds (Region 4).

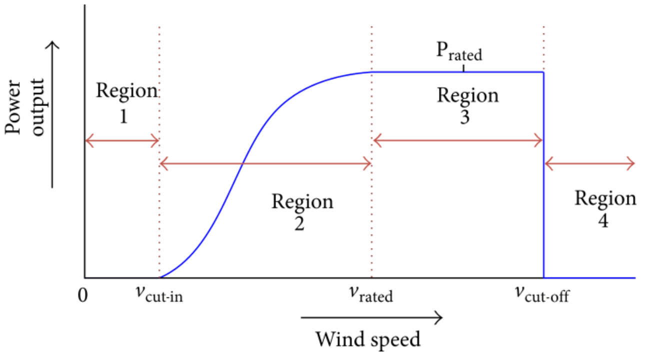

Fig. 1. Operating regions of a wind turbine power curve [9]

Despite of their effectiveness in the condition monitoring, wind turbine power curves include the plenty of outliers in the SCADA data and it is needed to detect and clean them [11]. As shown in Fig. 2, this abnormal data is categorized into three types as stacked outliers, scattered outliers and negative outliers [12, 13]. Type I data points are the negative outliers caused by wind curtailment, wind turbine failures and unplanned maintenance. Type II data points are the scattered outliers caused by uncontrolled coincidental factors, sensor noises and faults. Type III data points are the stacked outliers caused by communication failures and wind curtailment commands.

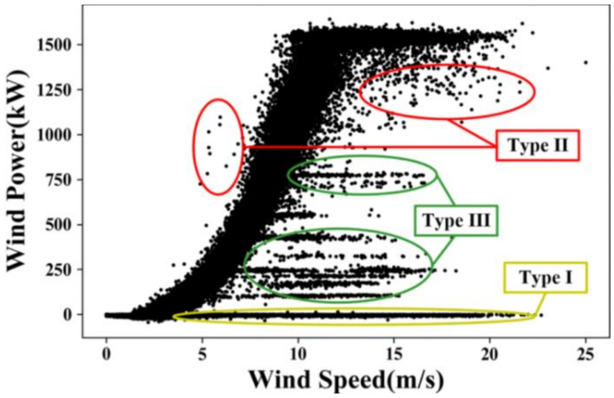

Fig. 2. Outlier types in a wind turbine power curve [12]

In this regard, this study briefly examines the outlier detection approaches used for wind turbine power curves. The current status of the corresponding literature has been summarized and the available problems needed to be worked out have been evaluated. In addition, many useful recommendations have been made for the characterization of wind turbine power curves (WTPCs).

II. OUTLIER DETECTION APPROACHES FOR WTPCS

The employed approaches have been compared in terms of the location and installed power of wind turbine/farm, the recording period and interval of total dataset, and the accuracy results. Table I presents this detailed comparison. For instance, in [18], a wind turbine, which is located in UK and has the installed power of 2 MW, was utilized. The total dataset was collected at 10-min intervals over the period of 2 months. Gaussian mixture copula model, Frank copula model and Gaussian mixture model were used to clean the outliers. Frank copula model provided better results than Gaussian mixture model in terms of Bayesian information criterion (BIC). Their BIC values were obtained as 112415 and 114993, respectively. Gaussian mixture copula model outperformed these two algorithms with the BIC value of 110597.

TABLE I. COMPARISON OF ABNORMALITY DETECTION METHODS FOR WIND TURBINE POWER CURVES

Ref.	Wind Turbine / Farm		Total Dataset		Employed Models	Results
	Location	Power	Period / Observations	Recording Interval		
[14]	China	25.5 MW (WF2) 30 MW (WF1)	30723 (Avg.) 91402 (Avg.)	10-min	k-means algorithm	AR: 0.92
					Local outlier factor algorithm	AR: 0.88
					Combination of change point grouping algorithm and quartile algorithm	AR: 0.92
					Adaptive confidence boundary modeling	AR: 0.81
					Image-based detection and cleaning algorithm	AR: 0.89
					Image thresholding based on minimization of dissimilarity-and-uncertainty-based energy	AR: 0.97
[15]	China	3 MW (WF1) 2 MW (WF2) 13.5 MW (WF3)	9 days (WF1) 1 year (WF2) ~3 months (WF3)	0.5-sec (WF1) 10-min (WF2) 1-min (WF3)	Intuitive rules method based on mechanism analysis	DDR: 16.71 - 45.01%
					Local outlier factor algorithm	DDR: 14.99 - 15.01%
					Partitional clustering-based algorithm	DDR: 3.74 - 30.57%
					Change point grouping-quartile algorithm	DDR: 8.68 - 22.53%
					Image-based algorithm	DDR: 12.95 - 36.53%
[12]	China	25.5 MW (WF1) 30 MW (WF2)	8 months (WF1) 19 months (WF2)	10-min	Image-based data cleaning algorithm	DDR: 8.93 - 22.33% (WF1) DDR: 8.28 - 24.92% (WF2)
					Local outlier factor algorithm	DDR: 9.89 - 9.99% (WF1) DDR: 9.91 - 9.97% (WF2)
					Combination of change point grouping algorithm and quartile algorithm	DDR: 5.12 - 13.32% (WF1) DDR: 5.78 - 13.01% (WF2)
					k-means algorithm	DDR: 10.17 - % 17.73(WF1) DDR: 3.73 - 7.52% (WF2)
[16]	China	30 MW (WF1) 25.5 MW (WF2)	30723 (Avg.) 91402 (Avg.)	10-min	Image processing	DDR: 38.10% (WF1) DDR: 35.88% (WF2)
					Mathematical morphology operation	DDR: 14.44% (WF1) DDR: 16.06% (WF2)
					Local outlier factor algorithm	DDR: 9.94% (WF1) DDR: 9.93% (WF2)
[17]	China	2 MW	12 months	10-min	Change point grouping-quartile algorithm	DDR: 21.04% (39.59s)
					Quartile-change point grouping algorithm	DDR: 27.10% (33.06s)
					Local outlier factor algorithm	DDR: 21.04% (15min27s)
[18]	UK	2 MW	2 months	10-min	Gaussian mixture copula model	BIC: 110597
					Frank copula model	BIC: 112415
					Gaussian mixture model	BIC: 114993
[19]	China	1.5 MW	3 months	5-min	Self-organizing maps	ER: 22%
					Linear mixture self-organizing maps	ER: 15%
[20]	China	6 MW	~3 months	10-min	Combination of stacked denoising auto-encoder and density-grid-based clustering method	CCR: ≅98%
					Local outlier factor algorithm	CCR: ≅86%
[21]	Scotland, UK	7 MW	1 year	1-sec	Elliptic envelope method	Isolation forest method
					Isolation forest method	
[22]	Chile	2 MW	52560	10-min	Gaussian process	DDR: 8.27%
[23]	China	48 MW	12 months	10-min	Combination of intuitive rules and density-based spatial clustering of applications with noise	PNOD: 38.94 - 59.32%
		49.5 MW				PNOD: 40.97 - 64.03%
[24]	China	3.5 GW	15 months	15-min	Combination of probabilistic wind farm power curve and outlier types	ODP: 10.21%
[25]	China	40 MW	15000	10-min	Combination of quartile method and density-based clustering method	DDR: 17.88%
[26]	China	150 MW	13811	15-min	Local outlier factor algorithm	ODP: 94.45%
[27]	Denmark	2 MW	8784	10-min	Combination of k-means, k-means++, k-medoids and k-medoids++ algorithms with Mahalanobis distance and chi-square cumulative distribution	NIO: 1150 (k-means) NIO: 1149 (k-means++) NIO: 717 (k-medoids) NIO: 539 (k-medoids++)
[28]	Iran	1.5 MW	1954	5-min	Modified hyperbolic tangent model	NIO: 258
[29]	Portugal	1.8 MW	50444	10-min	Combination of Betz limit, quartile criteria and histogram analysis	NIO: 3009
[30]	Scotland, UK	7 MW	744	1-h	Isolation forest method	CR: 14%
[31]	Scotland, UK	7 MW	9 months	10-min	Isolation forest method	CR: 4%
[32]	China	1.5 MW	3 months	10-min	Combination of genetic algorithm based on partial least squares regression and back propagation neural networks	-
[33]	China	24 MW	497838	10-min	Combination of k-means clustering, Tukey's method and threshold limit	-
[34]	Ecuador	16.5 MW	1 year	10-min	Robust confidence band	-
[35]	Spain	17.56 MW	5.5 days	10-min	Combination of automatic clustering and T^2 statistic	-

TABLE I. COMPARISON OF ABNORMALITY DETECTION METHODS FOR WIND TURBINE POWER CURVES (*CONT.*)

Ref.	Wind Turbine / Farm		Total Dataset		Employed Models	Results
	Location	Power	Period / Observations	Recording Interval		
[11]	USA	100 MW	2 months	10-sec	Combination of T^2 chart, generalized variance chart and individual-moving range chart	-
[36]	-	1.5 MW	12 months	5-min	Piece-wise linear model	NIO: 2260
[37]	UK	-	125 weeks	10-min	Extreme function theory	CER: 0.125
					Point-wise Gaussian process	CER: 0.13
					Gaussian process with Monte Carlo threshold	CER: 0.32
					Gaussian process with differential evolution threshold	CER: 0.37
					Multivariate extreme value theory	CER: 0.23
					Auto-associative neural networks	CER: 0.17
[38]	North Sea, UK (WF1) Northern Europe (WF2)	-	24 months (WF1) 18 months (WF2)	10-min	Isolation forest method	ODP: 27.47%
					Gaussian mixture modeling	ODP: 15.13%
					Local outlier factor algorithm	ODP: 11.74%
					k nearest neighbours	ODP: 7.99%
[39]	China	-	3 months (WF1) 5 months (WF2) 9 months (WF3)	10-min	Gaussian process	5 parameter-logistic function based on quantile regression
					Density-based spatial clustering of applications with noise	
					Logistic functions based on quantile regression	
[40]	Spain	-	6 months	10-min	Binned linear least median of squares method	ODP: 96.01%
					Exponential least median of squares method	ODP: 96.39%
[41]	China	-	8 months (WF1) 19 months (WF2)	10-min	Combination of color space conversion and image feature detection	DDR: 8 - 14%
[42]	Northern China	-	1 year	15-min	Iterative regression process	RER: 40.74%
[43]	South America	-	2 years	10-min	Combination of data binning and Mahalanobis distance	DDR: ~5-6%
[44]	Southern Denmark	-	2 months	10-min	Combination of k-means algorithm, Mahalanobis distance and heuristic hard threshold	MR: %16
[45]	USA	-	4347	10-min	Combination of residual theory and control chart approaches	NIO: 156
[46]	North China	1.5 MW	-	-	Combination of mechanism cleaning, Gaussian mixture model and optimized multidimensional quartile method	PCC: 0.9721
[47]	-	-	1 year	10-min	Median statistics	NIO: 15214 (WT1) NIO: 14871 (WT2) NIO: 17336 (WT3) NIO: 16046 (WT4)
[10]	China	-	5500 (WT1) 6500 (WT2) 7500 (WT3) 6000 (WT4)	-	Combination of fuzzy c-means clustering and Mahalanobis distance	-
[48]	-	25.5 MW	-	-	Mathematical morphology operation	DDR: 8.93 - 22.33%
					Local outlier factor algorithm	DDR: 9.89 - 9.99%
					Combination of change point grouping algorithm and quartile algorithm	DDR: 5.12 - 13.32%
					k-means algorithm	DDR: 10.17 - 17.73%
					Image thresholding	DDR: 11.62 - 48.31%
[49]	-	-	2 years	10-min	Density based spatial clustering of applications with noise	-
[50]	Spain	-	-	-	Least median squares method	-

Abbreviations: AR (Accuracy Rate), AVG (Average), BIC (Bayesian Information Criterion), CR (Contamination Ratio), CCR (Correct Classification Rate), CER (Classification Error Rate), DDR (Data Deletion Rate), ER (Error Rate), MR (Misclassification Rate), NIO (Number of Identified Outliers), ODP (Outliers Detection Percentage), PCC: Pearson Coefficient, PNOD (Proportion of Normal Operational Data), RER (Relative Error Reduction), WF (Wind Farm), WT (Wind Turbine).

In Table I, on the basis of power plant types, wind farm-based ones enable to identify a greater number of outlier types than wind turbine-based ones. In case of considering the total dataset characteristics, there are different recording periods (24 months, 12 months, 8 months, 3 months, 2 months, etc.) along with different recording intervals (1-h, 15-min, 10-min, 5-min, 1-min, 1-sec, etc.). At least, a dataset recorded at 10-min intervals over a 12-month period should be used to include the seasonal effects. Within the employed models, local outlier factor (LOF) algorithm, Gaussian process-based (GPB) methods, image processing-based (IPB) methods and k-means algorithm are the commonly-used ones. Change point grouping-quartile (CPQ) algorithm, Mahalanobis distance (MD) and isolation forest (IF) method follow them. The outlier detection performance of all these models should be extensively compared in future studies. In the presentation of results, data deletion rate is the mostly-utilized measure. Number of identified outliers and outliers detection percentage are also frequently used. All of these measures should be employed in each future study for easy-to-comparison results. Lastly, any missing data related to the location and installed power of wind turbine/farm, the recording period and interval of total dataset and the accuracy results should be avoided.

III. Conclusions

The reliability of wind turbine power curves is adversely affected from the abnormalities in the SCADA data. Such abnormal data is required to be identified for the proper reflection of power generation performance of wind farms/turbines. In this study, a detailed comparison of outlier detection approaches in the literature has been conducted for discussing the cons of current studies and the pros of future studies. As a crucial result of this comparison, the outlier identification performance of LOF, GPB, IPB, k-means, CPQ, MD and IF methods is needed to be evaluated in terms of the measures of DDR, NIO and ODP. In addition, different combinations of these methods can also be created for novel hybrid models. In such benchmark studies, the use of raw power curve data collected from a wind farm at 10-min intervals over a year will be beneficial to build the models that are more sensitive to the outliers.

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