Title: A survey on the most practical signal processing methods in conditional monitoring in wind turbines

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Abstract

In the previous paper, diverse data acquisition methods based on data types for condition monitoring wind turbines is explored. The present study investigates advanced signal processing techniques in the field of condition monitoring of wind turbines. Methods include synchronous sampling, signal decomposition, envelope analysis, statistical evaluation, model-based approaches, Bayesian methods, and artificial intelligence techniques. Comparison and analysis of these methods and their applications in wind turbine fault detection and diagnosis are presented in this coming study. Moreover, the survey encompasses innovative approaches using various data sources, addressing challenges in components like bearings, gearboxes, blades, and generators. Insights into the evolution of data-driven decision-making in the wind energy sector are provided, with a focus on strengths, limitations, and future directions. A summarized table offers an overview of studies, highlighting monitored components, data types, and methods.

Keywords: wind turbine, conditional monitoring, fault prediction, artificial intelligence (AI)

I. Introduction

In the realm of equipment condition monitoring, the path from data acquisition to actionable insights demands a nuanced approach. In the previous paper, diverse equipment monitoring methods based on data types is explored. Here, the authors delve into a pivotal aspect of signal processing methods. These techniques, including synchronous sampling, signal decomposition, envelope analysis, statistical analysis, model-based methods, Bayesian methods, and AI-based methods, are crucial for deciphering complex signals, especially in non-stationary contexts like wind turbines.

Section II unveils the principles, strengths, and limitations of each method, offering a view of their roles. In section III, a survey of research focused on wind turbine fault detection, and isolation is presented. Finally, in section IV, the conclusion is proposed.

II. Conditional Monitoring: Signal processing method

In the previous part, the types of equipment condition monitoring methods based on data types were explained. It is necessary to process the data for fault detection and to identify the characteristics associated with each piece of equipment. In this section, the most practical and widely used signal processing method will be presented.

It is well known that the signals from wind turbines due to fluctuations in wind speed are non-stationary signals [1]. This issue makes it difficult to use classic signal processing methods, and therefore it is necessary to choose appropriate methods. The most widely used and practical signal processing methods are as follows that' scheme is shown in Figure 1:

- synchronous sampling
- Signal decomposition
- Envelope Analysis
- Statistical analysis
- Model-based methods
- Bayesian methods
- AI-based Methods

A. Synchronous sampling

Due to the non-stationary nature of the signals from the wind turbine, it is not possible to use classical methods based on the frequency spectrum of signals. In this method, short and suitable time windows are first considered, then the Fourier transform (as given in Equation (1)) is applied to obtain the frequency spectrum of the signals within that time window. Based on the resulting diagram, the characteristics and frequency characteristics of the faults are determined.

(1)

Where $X(j\omega)$ Is the Fourier transform of $x(t)$ function.

Frequency analysis methods based on synchronous sampling have higher resolution in the frequency domain compared to time-frequency domain analysis methods and are computationally efficient for use in online wind turbine condition monitoring, such as the wavelet transform or short-time Fourier transform [2].

B. Signal Decomposition

In this method, the non-stationary signal is first converted into several sub-signals using techniques such as wavelet transform, Empirical Mode Decomposition (EMD), etc. Then, the important characteristics of the sub-signals are identified through time or frequency analysis.

a. Wavelet Transform

The wavelet transform is a mathematical technique that decomposes a signal by controlling the scale and converting the original wavelet factors into several lower-resolution levels using equation (2) as follows:

(2)

Where X_ω Is the wavelet transform of the signal, a is the scale factor, b is the shift factor, ψ is the mother signal, & $x(t)$ is the main signal.

The fundamental concept of the wavelet transform involves breaking down a signal into a group of frequency channels that possess identical bandwidth on a logarithmic scale in a hierarchical manner [2]. The wavelet transform is divided into two main categories: 1) Continuous wavelet transform, and 2) Discrete wavelet transform, which depend on whether the a and b parameters are continuous or discrete. The wavelet transform has an advantage over the Fourier transform in that it can be used for any type of signal in both the time and frequency domains simultaneously [3]. However, one of the most significant challenges with this method is choosing the appropriate mother wavelet, as a poor choice can reduce its accuracy and computational efficiency.

b. Empirical Mode Decomposition

In this method, the original signal is divided into several sub-signals while retaining the basic characteristics of the original signal, such that the sum of the sub-signals is equal to the original signal. Typically, the characteristics of the original signal are extracted using the Hilbert transform or the Fourier transform [4]. One of the key advantages of this method is its ease of implementation and ability to be used with any type of signal. However, this method is very sensitive to noise and also integrates the modes of the system, making it difficult to extract the main features of the signal [5].

C. Envelope Analyses

This method uses a smooth function to detect anomalies by distinguishing parts of the signal that have a very large amplitude compared to other parts. The envelope analysis is a widely used and effective technique that has been incorporated into many commercial wind turbine condition monitoring systems (WT CMSs). The envelope of a signal is a time-domain signal that typically needs to be subjected to additional signal processing methods [2].

D. Statistical analysis

In this method, statistical parameters of the signal such as average, root mean square, kurtosis, and skewness, etc. are measured in the healthy operating mode. Then, by monitoring the equipment and measuring the statistical parameters during operation, it is compared and evaluated against its healthy operation [6].The statistical analysis methods are established and straightforward to apply. But, these methods typically only identify the existence of a fault in a wind turbine (WT) or subsystem of WT, and they rarely provide detailed information about the fault's mode or location. Additionally, the statistical methods are susceptible to noise, which limits their effectiveness in high-noise environments [7].

E. Model-Based Methods

In this method, the dynamic behavior of the equipment is modeled using accurate mathematical models. The parameters obtained from the model are then compared with the measured values of the equipment. If there is a difference outside the predefined range, the fault, and its occurrence will be detected in the equipment. The effectiveness of this method depends on the accuracy of the mathematical model, and as it is known, a comprehensive and accurate model cannot be obtained in reality due to uncertainties [8]. This method is also not usually able to detect the type of fault or its modes and is only used to detect the occurrence of a fault. Its scheme is shown in Figure 2[9].

F. Bayesian methods

Bayesian networks are a graphical model used to estimate probabilities. The model consists of nodes representing random variables with distinct states, connected by directional arcs representing conditional dependencies [10]. Bayesian networks can assess the likelihood of different scenarios as the root cause of an event or predict probabilities for future events [11]. Markov models, Kalman filters (KFs), and particle filters such as the particle filter Chebyshev are commonly used Bayesian techniques in engineering for prediction. Its Hieratical chart is shown in Figure 3.

a. Markov model

Markov models are used to predict future failure probabilities by determining the probabilities associated with each state and the transitions between them. These models have the characteristic that future states depend only on the preceding state. To utilize Markov models for prediction, certain assumptions are taken into consideration [12]:

- Transition probabilities are independent of time, meaning that the failure rate is constant.
- The waiting time in a particular state follows an exponential trend.
- The sum of all transition probabilities for leaving one state and entering different states must equal one [13].

On the contrary, the Hidden Markov Model (HMM) is an advancement of Markov chains where certain states are not directly observable, hence transition probabilities cannot be directly determined. An HMM is described by the number of model states, the number of observation symbols per state, a probability distribution for state transitions, a probability distribution for observation symbols, and an initial state distribution [12]. HMMs possess the advantage of modeling both spatial and temporal phenomena and can analyze time-series data without comprehending the failure physically, as long as enough data is present for training. However, a drawback of all types of Markov models is their computational complexity. The number of computations required to evaluate the accuracy of the model fitting the observation dataset is proportional to the number of states squared [14].

b. Filters

Kalman Filters (KFs) are iterative algorithms employed to predict the hidden state of a dynamic system using imprecise measurements. The algorithm estimates the state by reducing the average squared error through linear projections [15].The method is predicated on the idea that the measurement and process noise are additive, white, and Gaussian, and are also independent of each other. Particle filters are a suitable alternative to KFs because they do not have the limitations of KFs. They are particularly well-suited for estimating the Probability Density Function (PDF) in the future for multivariable and non-standard problems [16].

G. Artificial intelligence

Artificial Intelligence (AI) is a collection of methods and techniques that allow a machine or computer to learn and imitate human behavior. AI can be broadly divided into three categories: 1) Machine learning, 2) Reinforcement learning, and 3) Neural networks. It's important to note that Deep learning is a subset of Machine learning. In this method, the machine is trained by providing input-output pairs. With sufficient examples, the machine learns how to perform the task, rather than being programmed with a specific mathematical formula [17].

a. Artificial neural network

Warren McCulloch and Walter Pitts were pioneers in the development of Artificial Neural Networks (ANNs) in 1943 [18]. Since then, there has been a growing interest in understanding the properties of ANNs. In 1985, John Hopfield's book [19] and the development of back-propagation ANN models by David Rumelhart and G. Hinton in 1986 [20] sparked more focused interest in ANNs for specific industrial applications. Neural networks are used in the following fields [21]:

- Association: A technique for reducing data dimensionality.
- Classification: A technique for grouping data into classes.
- Conceptualization: A technique for creating concepts based on concrete data.
- Prediction: A technique for forecasting future values.
- Optimization: A technique for finding the minimum solution.
- Filtering: A technique for sorting data based on certain criteria.

Table I Table I displays a list of the early contributions to Artificial Neural Networks (ANNs).

Considering the numerous types of neural networks that have been developed to date, they primarily differ in their structure, data flow direction, type of neuron employed, density, number of layers, and types of activation functions. Figure 4 illustrates the fundamental architecture of a neural network.

1. Perceptron

The Perceptron is the simplest and oldest model of a neuron, which receives two inputs, combines them, applies an activation function, and finally forwards the result to the output layer [22]. This network structure is shown in Figure 5.

2. Feed Forward Neural Networks

One of the older members of the Neural Network family is the Feed-forward Neural Network, with its approach dating back to the 1950s [23]. The function of this algorithm typically follows these rules:

- Every node is connected to all other nodes in the network.
- Data flows only in a forward direction from the input layer to the output layer.
- There is a layer called the "hidden layer" located between the input and output layers.

The back-propagation algorithm is frequently used to train this type of neural network [24] [25].

3. Recurrent Neural Networks

Recurrence neural networks utilize recurrent cells, a type of cell distinct from those used in feed-forward neural networks [26].The Jordan network, the first of this type of network, includes hidden cells that receive their output after a delay of one or more iterations [27].

4. Hopfield Networks

Hopfield networks are designed to respond to a known input with a similar output, and are trained on a limited set of examples. Each cell in the network serves as an input cell before training, a hidden cell during training, and an output cell during use. The primary objective of these networks is to create trained examples [28]. They are commonly used to complete input sequences or images, and can return the full sample when given half of a learned image or sequence [29].

5. Boltzmann Machines

Boltzmann machines and Hopfield networks share similarities in that they both contain cells marked as input and remain hidden, with input cells becoming output cells once the hidden cells update their state. However, Boltzmann machines are more complex than Hopfield networks as they allow for bidirectional connections between nodes, while Hopfield networks only allow unidirectional connections. Boltzmann machines also use stochastic techniques to update the state of their nodes, allowing them to explore a wider range of possible solutions [30] [31]. During training, the Boltzmann machine updates the cells one by one, not in parallel [32].

5.1. Restricted Boltzmann Machine

A restricted Boltzmann machine is similar in structure to a Boltzmann machine but is more limited [33]. It can only be trained using back-propagation and acts as a feed-forward network, with the only difference being that post-release referenced data is returned to the input layer once [34].

b. Machine Learning

Machine learning is a field of artificial intelligence that focuses on teaching machines to improve their performance based on past data and make predictions [35]. It consists of a set of algorithms that are applied to large amounts of data, with the goal of producing a model. This model is then used for various tasks, such as classification, clustering, and prediction. There are three primary categories of machine learning algorithms: supervised, unsupervised, and deep learning [36].

1. Supervised Algorithms

In this method, the training dataset includes appropriate input and output values. A machine learning model is created that adjusts its variables to represent the corresponding input-output mapping. Supervised machine learning is further divided into two groups: classification and regression [37].

1.1. Classification

Classification algorithms are employed to tackle classification problems, where the output variable or label comprises values like "yes" or "no," "male" or "female," "red" or "blue," and so on [38]. Common classification algorithms include:

- Random Forest Algorithm [39]
- Decision Tree Algorithm [40]
- Logistic Regression Algorithm [41]
- Support Vector Machine Algorithm [42]
- Artificial Neural Network Algorithm

1.2. Regression

Regression algorithms are utilized to address regression problems in which a linear association exists between input and output variables. These algorithms are implemented to anticipate continuous output variables, like forecasting stock or weather [43]. Some of the common regression algorithms include:

- Simple Linear Regression Algorithm [44]
- Multivariate Regression Algorithm [45]

2. Unsupervised Algorithms

In unsupervised learning, the focus is not on producing outputs, but on classifying data into different groups [46]. It is divided into two categories.

2.1. Clustering

Clustering is a technique used to identify intrinsic groups in data, where objects within a cluster are more similar to each other and less similar to objects in other clusters [47]. Some popular clustering algorithms are listed below [48].

- K-Means
- Density-Based Spatial Clustering of Applications with Noise
- Hierarchical Clustering Algorithm

2.2. Association

Associative rule learning is a type of unsupervised learning that identifies meaningful relationships between variables within vast datasets. The main objective of this machine learning technique is to uncover the interdependence between data items and to establish mappings between variables that lead to maximal benefits [49]. This algorithm is mainly used in market portfolio analysis and some common algorithms for learning associative rules include:

- Apriori Algorithm [50]
- Eclat Algorithm [51]
- FP-Growth Algorithm [52]

c. Deep Learning

Deep learning is a subfield of machine learning that models the structure and functionality of the human brain. These algorithms are designed to learn autonomously, using artificial neural networks that emulate the brain's information processing. During the training process, these algorithms utilize unknown elements in the input to identify features, group objects, and detect patterns in the data. Deep learning models often consist of multiple algorithms, each tailored to specific tasks [53]. Some of the most commonly used types include:

- Convolutional Neural Networks [54]
- Long Short-Term Memory Networks [55]
- Recurrent Neural Networks
- Generative Adversarial Networks [56]
- Radial Basis Function Networks [57]
- Multilayer Perceptron [58]
- Self-Organizing Maps [59]
- Deep Belief Networks [60]
- Restricted Boltzmann Machines
- Auto-Encoders

d. Reinforcement Algorithms

These algorithms are trained based on decisions, so their performance depends on the decisions made during training. Ultimately, the algorithms gain experience and are capable of producing successful outputs [61]. Reinforcement learning is a machine learning technique that works through a feedback loop in which an AI agent interacts with its environment and takes actions. The agent is rewarded for good actions and penalized for bad ones, with the aim of maximizing its reward and improving its performance through feedback. In contrast to supervised learning, reinforcement learning does not rely on labeled data, and the agent learns solely from its own experiences [62]. The process is similar to human growth and development, where a child learns through experiences in daily life. Reinforcement learning is a versatile approach that can be applied in a range of fields, including game theory, operations research, information theory, and multi-agent systems, due to its distinctive learning process [63].

1. Fuzzy Logic Systems

Fuzzy logic systems are often used to detect faults in generators and wind turbine pitch systems [64]. These systems are trained by the characteristics of various faults, and fuzzy rules are developed to monitor equipment conditions. However, the design of fuzzy rules depends on a complete understanding of the mechanism of different parts in the wind turbine, which is not feasible in reality. Incorrect fuzzy rule design can result in incorrect diagnoses [64]. It is important to note that the system dimensions increase exponentially with the number of faults, making the cost of calculations heavy, which is one of the disadvantages of this method [65].

The comparison of Bayesian network methods with methods based on artificial intelligence is presented in Table II, and a comparison of the most popular methods is presented in Table III.

III. Conditional monitoring: literature review (wind turbine)

Over the past twenty years, there has been significant research activity in the field of wind turbine condition monitoring. This part discusses various research studies and methods related to fault diagnosis and condition monitoring in wind turbines. The authors of the different references propose innovative approaches and techniques to address specific challenges in detecting and diagnosing faults in wind turbine components, such as bearings, gearboxes, blades, generators, and electrical systems. The methods utilize different data sources, including vibration signals, acoustic emission, stator current, SCADA data, and more. The studies employ various tools and algorithms, such as statistical analysis, wavelet analysis, neural networks, empirical mode decomposition, support vector machines, and deep learning models. The aim of these research efforts is to improve the effectiveness and efficiency of fault detection, localization, and diagnosis in wind turbine systems, enabling early detection and proactive maintenance to prevent breakdowns and optimize turbine performance.

Authors in [66] propose a novel diagnostic approach for condition monitoring of bearings used in wind turbines, addressing the challenges posed by non-stationary load conditions. The method utilizes input data obtained from a commercial diagnostic system and incorporates load susceptibility characteristics (LSCh) to remove the dependency on operating conditions. The study includes case studies of bearing failure and significant condition changes, highlighting the need for suitable data presentation and statistical processing (linear regression analysis) for long-term monitoring and decision-making. In [67], authors diagnose rolling element bearing faults in a wind turbine gearbox using vibration analysis, acoustic analysis, and lubrication oil analysis. Statistical features are extracted from wavelet approximation coefficients, and an integrated condition monitoring scheme combining these techniques demonstrates better fault diagnosis capabilities compared to individual techniques.

Reference [68] introduces a novel approach for fault detection in rotating machinery by maximizing the sparsity of the envelope spectrum. Blind filters are derived using different sparsity measures, enabling effective tracking of faults with cyclostationary signatures without prior knowledge of characteristic fault frequencies

Reference [69] addresses fault diagnosis of wind turbine blades by performing continuous structural health condition monitoring. Statistical features are extracted from vibration signals, feature selection is conducted using a J48 decision tree algorithm, and feature classification is performed using the best-first tree and functional trees algorithms to determine the most effective approach. In [70], the Authors explore the application of vibration-based artificial neural networks (ANNs) for damage assessment in wind-turbine towers. Modal parameters are used as inputs, and element stiffness indices are the outputs. The ANNs are trained using a finite element model of a real wind turbine tower and are capable of detecting damaged elements and assessing their severities. Reference [71] proposes an optimized vibration-based fault detection method for offshore wind turbine drivetrains. By analyzing simulated shaft acceleration measurements, it is determined that only two vibration sensors, placed near the main and intermediate-speed shafts, are needed to accurately detect faulty bearings. Axial vibration data outperforms radial data, and the approach can be applied to virtual digital twin models.

Reference [72] proposes an unsupervised time-series anomaly detection method for wind turbine nacelles. It combines deep learning with multi-parameter relative variability detection and validates its effectiveness using real-world wind farm data.

Reference [73] proposes a noninvasive technique for diagnosing gear tooth surface damage faults based on stator current analysis. The fault signature is identified through torque oscillation profiles and fault-related frequencies in the stator current. Reference [74] proposes a method for detecting gearbox faults in wind turbines using non-stationary stator current signals. It identifies characteristic frequencies of gearbox faults and presents a fault detection approach that includes adaptive signal resampling, statistical analysis, and fault detectors. Reference [75] presents a fault diagnosis algorithm for a 25-kW wind turbine drivetrain. It focuses on detecting and locating defects in the generator rotor and gearbox pinion. Using signal processing techniques, such as wavelet packet transform and local mean decomposition with Fast Fourier Transform, gear teeth faults are identified based on the detection of gear meshing frequency in the stator current. Principal component analysis is employed for classification of gearbox states. Despite limited data, significant results are obtained

Reference [76] explores the use of acoustic emission (AE) analysis for diagnosing slow-speed wind turbine blade bearing faults. A novel cepstrum editing method called DRS-CEL is proposed to denoise raw AE signals, and morphological envelope analysis is applied for further noise filtering and fault type inference. In reference [77], researchers propose a new method for localizing faulty planet gears in wind turbine gearboxes using acoustic emission (AE) techniques. The method focuses on obtaining precise time of arrival for AE signals and utilizes continuous wavelet transform based on the Morlet wavelet to extract compressive waves. Reference [78] uses acoustic emission (AE) analysis to diagnose faults in a slow-speed wind turbine blade bearing. The challenge is filtering raw AE signals to extract weak fault signals. The proposed method involves a general linear and nonlinear auto-regressive (GLNAR) model to capture nonlinear characteristics and the SAL algorithm for signal filtering. Resampling is used to diagnose the fault type. Reference [79] introduces a novel approach for early-stage and low rotational speed rolling bearing fault diagnosis using a generative adversarial network (GAN)-based data enhancement. By utilizing acoustic emission (AE) signals, the proposed method overcomes the challenges of limited training data and data imbalance issues, and achieves superior performance compared to traditional methods such as SVM and CNN models.

In reference [80], the combination of neural networks and the analysis of five experimental scenarios, including 1) Aerodynamic asymmetry, 2) Turbine rotation imbalance, 3) Turbine boundary imbalance, 4) Nacelle imbalance, and 5) The non-use of software in the normal operation mode of the permanent magnet wind turbine generator, has been utilized for fault diagnosis in wind turbines using the stator current. In reference [81], fault detection in wind turbine gearboxes has been performed using diagonal spectrum and binary clustering tree Support Vector Machines. In reference [82], more models related to bearing and gearbox fault detection using the wavelet method and neural networks are presented. Additionally, other works in this field have explored the use of convolutional neural network methods in [83], [84]. Furthermore, the Local Mean Decomposition (LMD) and neural network are investigated in [85], while a back-propagation neural network is utilized in [86]. Moreover, an improved back-propagation neural network (IBPNN) is employed in [87], and a back-propagation neural network (BPNN) trained with the PSO algorithm is utilized in [88].

Reference [89] proposes an extended Kalman filter (EKF) based method to detect rotor electrical asymmetry in wind turbine doubly fed induction generators (DFIGs). The method effectively estimates and tracks fault signature components (FSCs) in time-varying current signals. Experimental results demonstrate the superiority of the EKF over other algorithms, such as continuous wavelet transform (CWT) and iterative localized discrete Fourier-transform (IDFT), in accurately diagnosing faults in different operating conditions.

In reference [90] A framework is proposed for quantitatively evaluating faults and health conditions in wind turbines using generator current signals. A resampling algorithm handles non-stationary signals for fault feature extraction. The extracted features are used to calculate correlation dimensions for fault and health condition evaluation.

Reference [91] proposes a fault diagnosis method for wind turbines based on integral extension load mean decomposition multi-scale entropy (IELMDME), and least squares support vector machine (LSSVM). The method effectively processes vibration signals, extracts characteristic parameters, and accurately classifies bearing fault types.

Reference [92] presents a new method for detecting and quantifying inter-turn faults in line start permanent magnet synchronous motors (LSPMSMs). The method uses convolutional neural networks (CNNs) to analyze the stator current during the steady-state period and accurately detect faults without separate feature extraction. Experimental results demonstrate high accuracy (97.75%) in fault detection across various loading conditions. The proposed technique enables online fault detection without disrupting system functionality or requiring additional hardware.

In reference [93], the support vector machine was utilized with SCADA training data to identify and predict faults in the following categories: 1) power supply, 2) cooling system, 3) generator excitation, 4) generator failure, and other basic faults. In this research, firstly, the correct operating mode has been separated from the faulty mode. Then, fault identification and prediction of the mentioned faults have been performed. In reference [94], the non-linear self-regression algorithm of the neural network, based on SCADA data, was used to detect bearing faults in wind turbine gearboxes. In reference [95], neural network methods were employed using SCADA data to detect main bearing faults in wind turbines.

Reference [96] presents a new approach using structural break detection in SCADA data for monitoring and diagnosing faults in wind turbines. The Chow test is adapted to assess the stability of regression coefficients in a temperature-based model. Any instability indicates a fault occurrence. Control charts and p-values are used to detect structural changes. The method is validated with known fault events, demonstrating its effectiveness in detecting abnormalities. In reference [97], the authors introduce a novel intelligent fault diagnosis methodology for wind turbines based on deep neural networks. The imbalanced distribution of SCADA data is addressed using a triplet loss approach that preserves within-class and between-classes information. The proposed method is validated using SCADA data from wind turbines with blade icing accretion faults, showing superior performance compared to traditional modeling methods.

In reference [98], authors present a scientometric review of the evolution of data-driven decision-making techniques, particularly artificial intelligence (AI) methods, in the wind energy sector. The review highlights the progress from signal processing to deep learning and explores the strengths, limitations, and future challenges of data-driven decision-making in wind turbine operations and maintenance (O&M). The article addresses issues such as data availability and quality, transparency of AI models, and real-time deployment. It concludes by emphasizing the importance of adopting data-driven approaches in O&M to enhance the reliability of wind energy and contribute to global sustainability efforts.

Studies proposed in this section are summarized in Table IV, including: monitored components, data types, and methods.

IV. Conclusion

The article discusses the importance of wind turbine maintenance in generating electricity to address the issue of global warming. It also highlights the challenges involved in their maintenance and operation. Proper planning and maintenance scheduling are crucial to minimize economic losses. The first section of this study that is published in a separate paper reviews solutions to manage these deficiencies and covers the types of data and methods used for data acquisition in the conditional monitoring of wind turbines. The second part of the study (present paper) discusses practical signal processing methods that can be employed in wind turbine conditional monitoring. The results are compared in

Table III. Lastly, the article examines several studies with various approaches in condition monitoring of wind turbines that is summarized in Table IV.

The majority of these approaches utilize vibration analysis, acoustic analysis, electrical parameter analysis, SCADA systems, sensors for data acquisition, and AI-based methods, as well as signal decomposition-based methods or a combination of them for signal processing. Additionally, the implementation of Fault Tolerant Control (FTC) is used to optimize wind turbine performance in the event of sensor failures. However, each method has its own limitations. The main challenges in these approaches are the availability of sufficient and appropriate data for data acquisition, as well as the computational burden associated with signal processing methods. The main advantages of these approaches are their high accuracy and the ability to model complex systems.

Therefore, future challenges in wind turbine maintenance include:

- Focusing on developing algorithms that require less data.
- Reducing the computational requirements of signal processing methods.
- Enabling the system to update the model with the occurrence of new conditions at any moment in time.
- Enabling early detection and proactive maintenance to prevent breakdowns the wind turbine.
- Reducing system maintenance costs.

By addressing these challenges, future approaches can be more effective, practical, and efficient for wind turbine maintenance.

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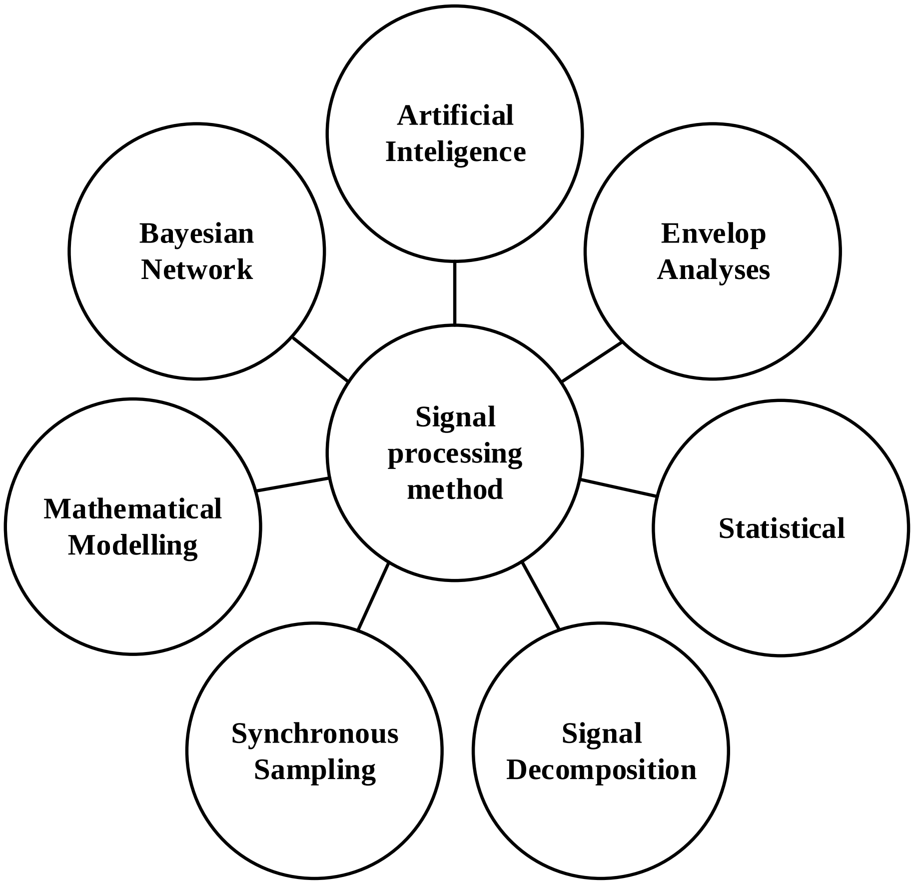

Figure 1: The most widely used and practical signal processing methods

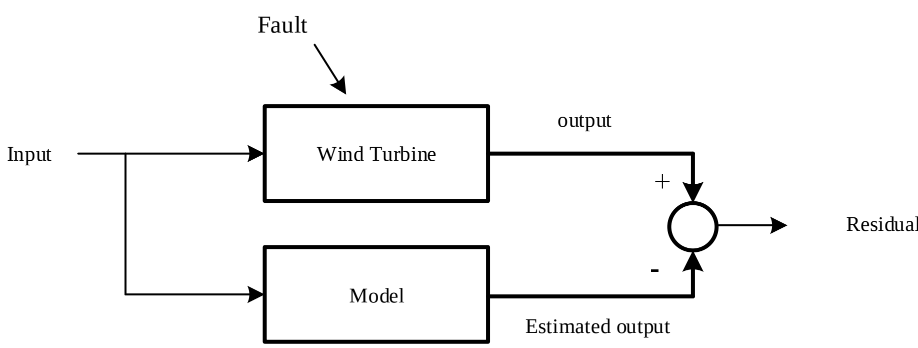

Figure 2: Model-based CMFD by analyzing the residual signal [9]

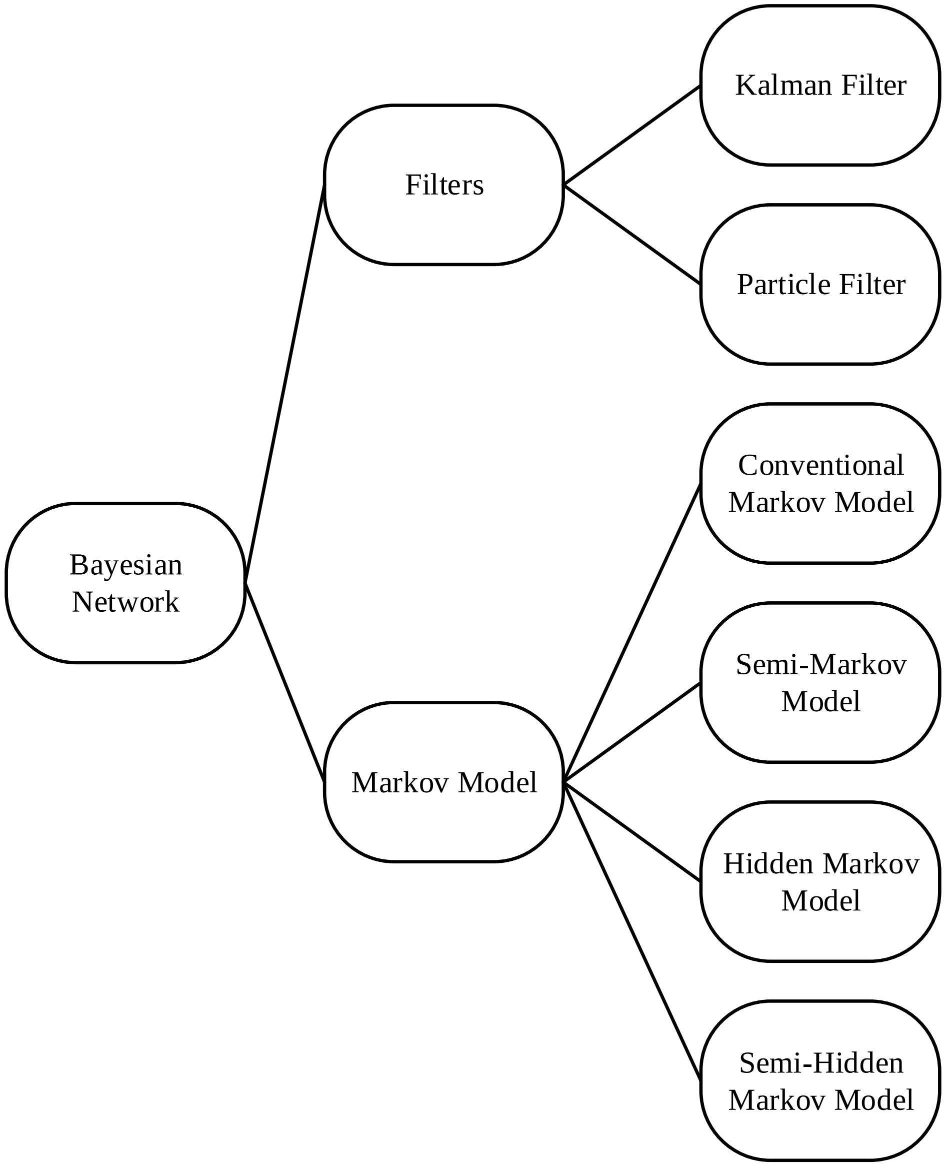

Figure 3: Hieratical chart of Bayesian Network

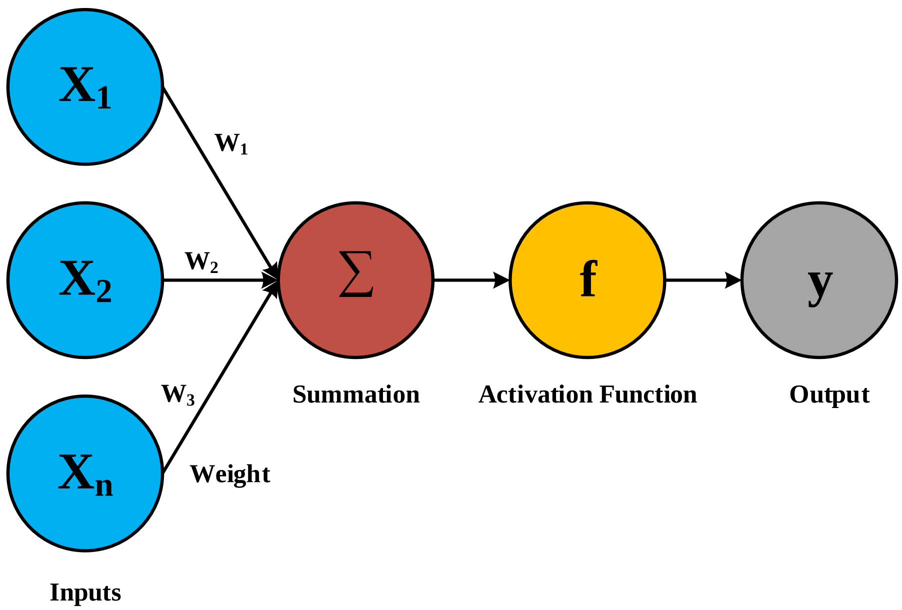

Figure 4: fundamental architecture of a neural network

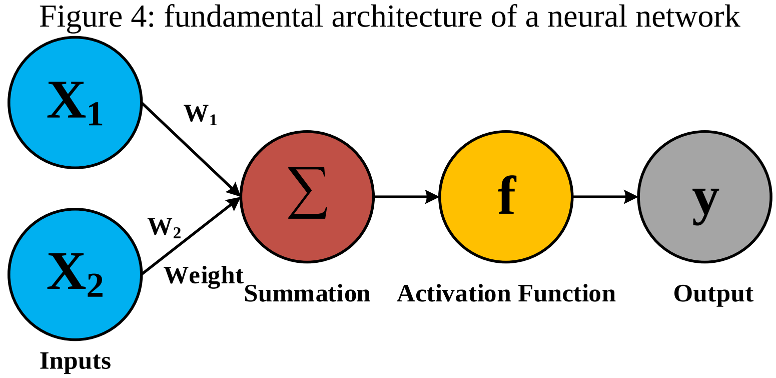

Figure 5: perceptron network

Table I: list of the early contributions to Artificial Neural Networks (ANNs)[21]

Num	ANN Model	Creator	Year	Utilization
1	Perceptron Networks	Rosenblatt	1958	Prediction
2	Adaline y Madaline	Bernard Widrow	1960	Prediction
3	Spatio-Temporal-Pattern Recognition (SPR)	Grossberg	1960–1970	Association
4	Adaptative Resonance Theory Networks (ART)	Carpenter, Grossberg	1960–1986	Conceptualization
5	Directed Random Search (DRS) Networks	Maytas y Solis	1965–1981	Classification
6	Brain State in a Box	James Anderson	1970–1986	Association
7	Self-organizing Maps (SOM)	Kohonen	1979–1982	Conceptualization
8	Hopfield Networks	Hopfield	1982	Optimization
9	Back-Propagation	Rumelhart y Parker	1985	Prediction
10	The Boltzmann Machine	Ackley, Hinton y Sejnowski	1985	Association
11	Bi-Directional Associative Memory (BAM) Networks	Bart Kosko	1987	Association
12	Counter-Propagation	Hecht-Nielsen	1987	Association
13	Hamming Networks	Lippman	1987	Association
14	Delta Bar Delta (DBD) Networks	Jacob	1988	Classification
15	Learning Vector Quantization (LVQ) Networks	Kohonen	1988	Classification
16	Probabilistic Neural Network (PNN)	Specht	1988	Association
17	Recirculation Networks	Hinton y McClelland	1988	Filtering
18	Functional-link Networks (FLN)	Pao	1989	Classification
20	Digital Neural Networks Architecture (DNNA)	Neural Semiconductor Inc.	1990	Prediction

Table II: Comparison of Bayesian network methods with methods based on artificial intelligence

Methods	advantages	disadvantages
AI	useful and effective in complex, non-linear, and high-dimensional problems	Requires a lot of data for training, heavy computation
Bayesian net	Simplicity in managing ambiguous, noisy, and incomplete data	Computational challenging in determining a prior unknown network
Markov model	Well-organized method, capable of modeling , various system designs and failure modes, capable of managing incomplete data sets, providing confidence limits as part of the RUL prediction	Considering a single monotonic and no temporal failure degradation trend, cannot model previously unanticipated faults and/or root causes
Kalman Filter	Capable of accommodating incomplete and noisy measurements	computationally intensive of variants for non-linear systems, easily divergence of some variants
Particle Filter	Suitable for state estimation in nonlinear dynamic systems with non-Gaussian probability sources	It requires a suitable number of samples and also more calculations than the Kalman filter

Table III: comparison of most populated signal processing methods

Methods	Advantages	disadvantages
Model base	Simplicity in implementation	Accuracy depends on the model
Bayesian	Simplicity in managing ambiguous, noisy and incomplete data	Knowing the basic network Need a lot of training data regarding hidden states
Ai	useful and effective in complex, non-linear, and high-dimensional problems and has high accuracy	Requires a lot of data & heavy computation
Signal decomposition	Implementation in time and frequency domain simultaneously computational efficiency, easy implementation	Select the main signal Noise tolerance, mode integration
Statistical Method	computational efficiency, reliable results and easy implementation	High noise sensitivity, can not to detect the fault location
Envelope Analyses	computational efficiency and easy implementation	High noise sensitivity, can not to detect the fault location

Table IV: recent studies summarizing (monitored component, data, methods)

Ref	Monitored Component(s)	Data Type(s)	Methods(s)
66	Bearing	Vibration	linear regression
67	Bearing	Vibration, Acoustic, Lubrication oil	Wavelet
68	Bearing, Gear	Vibration	Envelope Spectrum
69	Blade	Vibration	Decision Tree
70	Tower	Vibration	ANNs
71	Drivetrains	Vibration	PCA-CNN
72	Nacelles	Vibration	Spectrum-Embedded Temporal Convolutional Network
73	Gear Tooth Surface	Stator Current	Harmonics Analyses
74	Gear box	Stator Current	Adaptive Signal Resampling
75	Generator rotor and Gearbox pinion	Stator Current	Wavelet, Local Mean Decomposition
76	Blade Bearing	Acoustic	Cepstrum, Morphological Envelope
77	Gearboxes	Acoustic	Wavelet
78	Blade Bearing	Acoustic	Auto-Regressive
79	Rolling Bearing	Acoustic	|Generative Adversarial Network
80	Main Shaft, Nacelle	Stator Current	ANN,EMD
81	Bearing, Gearboxes	Vibration	Diagonal Spectrum, Binary Clustering Tree SVM
82	Bearing, Gearboxes	Vibration	Wavelet , ANN
83	Gearbox	Vibration	Wavelet , CNN
84	Main Shaft, Bearing	Vibration	CNN
85	Bearing	Vibration	LMD,ANN
86	Main Shaft, Bearing	Vibration	Wavelet, ANN
87	Bearing	Vibration	IBPNN
88	Gearbox	Vibration	BPNN,PSO
89	Rotor Current winding	Rotor Current	EKF
90	Rotor	Generators Currents	Resampling
91	Bearing	Vibration	IELMDME, LSSVM
92	Stator Winding	Stator Current	CNN
93	Cooling System, Generator, Generator Excitations	SCADA	SVM
94	Bearing	SCADA	Non-Linear Self-Regression of NN
95	Bearing	SCADA	ANN
96	Wind turbine	SCADA	Regression Coefficients
97	Blade	SCADA	Deep NN

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