Research on Hybrid Renewable Energy Systems with Fault Detection Technology

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Abstract: Early and accurate fault detection and diagnosis for renewable energy systems can increase their safety and ensure the continuity of their service. This paper presents a comprehensive review of different fault detection and diagnosis methods for hybrid renewable energy systems consisting of a wind turbine power generator, a PV (photovoltaic) array, a PEM (polymer electrolyte membrane) fuel cell and a battery storage system. The need of batteries to store the generated power from the solar panel, wind turbine or PEM fuel cell is also emphasized. Finally, an overview of the current methods used in the diagnosing of the lead-acid battery degradation is given.

Key words: Fault detection, renewable energy systems, wind turbines, PV arrays, PEM fuel cells, lead acid batteries.

1. Introduction

Fault detection techniques are becoming crucial in renewable energy systems [1]. They offer prevention of components failure, reduction of maintenance cost, detection of degradation and thus increase the performance, efficiency, reliability and safety of these systems. They also provide detailed information on the performance and operation of the systems and solve the problem of short lifetime of equipments arising with excessive maintenance [2]. In general, fault is defined as departure from an acceptable range of an observed variable to a calculated parameter associated with a process [3]. There is abundance of literature on research work for fault diagnosis. Some classified fault diagnosis methods into three general categories, knowledge based methods, analytical model based methods and signal based methods as shown in Fig. 1. Other depending on the knowledge used and the nature of information processing, classified fault diagnosis

methods as quantitative model-based methods, qualitative model-based methods and process history based method. For each of these methods, there exist several underlying techniques for fault diagnosis.

2. Fault Detection and Diagnosis of Wind Turbine Power Generators

Wind energy has been the fastest renewable energy source in terms of installation. Yet the competitiveness of wind energy is intensified by the relatively high cost of operation and maintenance of these systems. The most efficient way of reducing these costs relies on condition monitoring and fault diagnosis of the WT (wind turbine) system. Faults can almost occur anywhere in this system and they can be classified into electrical faults such as transformer overheating, converter failure, stator winding short circuit, and generator faults, electronic faults in sensors and in electronic cards and mechanical faults mainly associated to the gearbox and the blades. Some of these faults occurs more frequently than others and yield more serious shortcomings [4].

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Fig. 1 Classification of fault diagnosis methods.

Most of the tools developed to detect faults in WT depend on the data collected from the installed sensors. The WT has a lot of sensors used to measure the vibration, temperature, speed, output power and generator current [5, 6]. For example, by analyzing the wind speed and the output power and comparing the real power output with the expected one, the overall health of the WT can be supervised. The analysis of the internal turbine components temperature associated to the power output curve also gives an image of the health of the components. The idea is to calculate the normal behavior expected for each of the monitored data types according to its current working and environmental conditions. As measurements from the WT are enormous; the use of neural networks was reported. Brandão et al. [7] gave an example on the detection of failure in the electric generator of a WT using a neural network. The neural network is trained using measured data from the WT to estimate or predict the temperature of the electric generator. To train a neural network, we need to collect data of a period of time with no faults occurring; thus, the neural network is trained to represent the normal operation of WT. Moreover, once any small change occurs in the WT, a new neural network needs to be trained. By calculating the mean absolute error between the expected normal temperature and the real measured one, we can predict faults in the generator.

Although thermal and vibration monitoring have been used for decades, many recent researches have been directed towards electrical monitoring using electrical quantities such as current, voltage and power,

like generator stator current, inverter output current or other electrical quantities depending on the fault studied. In Ref. [8], spectral analysis of the generator stator current was done using stationary and non-stationary signal processing methods to extract the frequency content and time-frequency information respectively of the discrete time generator current signal used to detect faults in a WT. Failure diagnosis based on frequency representation (periodogram and Welch periodogram), time-frequency representation (spectrogram) and time-scale analysis (scalogram) revealed the addition of frequency harmonics to the generator stator current spectrum in presence of faults like air-gap eccentricity, broken rotor bars and bearing damage. As compared to periodogram and Welch periodogram, the spectrogram and the scalogram, bring up major information concerning the time occurrence of the fault and exhibit better signal-to-noise. In Ref. [9], FFT was used to detect inverter fault in the WT. The DC side current component, stator current, inverter output current, and rotor current were analyzed using FFT. Then the fundamental frequency and the DC component were obtained to detect the presence of fault.

Finally, it is worth mentioning that many of the methods used in condition monitoring and fault detection in WT are inspired from electric motor condition monitoring. Recently, it has been demonstrated that many failures in the lead to stator current modulation. Amirat et al. [10] focused on mechanical failures that lead to stator current AM (amplitude modulation). The Concordia transform (Park's vector analysis) and Hilbert transform were used for current demodulation; faults were detected based on the difference in demodulated current between healthy and faulty generator.

3. Fault Analysis of PV Arrays

PV power generation has been applied more and more widely for its short construction period, ease of installation, safe, without noise, free of pollution use. Yet, to ensure safe and reliable operation of PV power

stations, it is imperative to establish a PV power station monitoring system for timely detecting and solving faults. Main faults in PV arrays are degradation of modules, short circuit in cell or module, open circuit in cell or module, and hot-spot (shadowing). There exist many fault detection methods for PV arrays. Some depend on the rearrangement of the connection of PV cells along with efficient installation of voltage and current sensors [11]. These sensors detect and localize faults in PV arrays using current-voltage measured data and compare it with nominal rated data. In Ref. [12], sensors were arranged in a way such that the fault branch can be detected by significant decrease in its output current and the concrete fault point of that branch can be located according to voltage analysis. Usually zero output current indicates an open-circuit fault. A decrease between 10% and 40% of the rated current normally indicates a short-circuit fault except for the hot spot phenomenon. For current drop more than 40% of the rated, hot spot can be determined.

Another fault detection method depends on infrared image analysis of the surface temperature of PV cells. The surface temperature of PV cells with fault differs from that of normally working PV cells, leading to an obvious difference between the two infrared images. Other than the need of an infrared imaging device, the main disadvantage is the impact of several environmental factors (other than faults) on the PV cell temperature and infrared properties. Maximum power point tracking can be used to track the output measurements at different times of the day so that to distinguish between output power decrease due to environmental factors or to faults. Chao et al. [13] proposed a model-based fault diagnosis of PV arrays. In Ref. [14], artificial neural network analysis was used. Cheng et al. [15] employed fuzzy control theory in PV systems; it proposes a calculation criterion that detects the difference between measured module current and expected current to alarm for a fault. In Ref. [16], the authors utilized electrical fault diagnosis methods such as the ECM (earth capacitance measurement) and the

TDR (time domain reflectometry).

4. Fault Detection of PEM Fuel Cell

PEMFC (polymer electrolyte membrane fuel cells) are energy systems that convert directly the chemical energy of hydrogen into electrical energy with high efficiency without CO₂ emission releasing only heat and water. However, PEMFC are still suffering from low reliability and short lifetime. Although a variety of design and control strategies have been proposed to improve the performance of PEMFC system, temporarily faults still might occur due to the complexity of the physical process and the functional limitations of some components such as membrane and electrodes. Faults in fuel cells can be mainly classified into degradation and drying of the membrane due to aging or due to operation incidents, fuel/gas starvation of the electrochemical reaction due to channel flow variation or to flooding, and leak of the membrane. All have a common consequence which is voltage drop.

Fuel cell diagnosis can be considered under different approaches, going from heuristic knowledge to mathematical models such as mechanistic model-based diagnosis, residual analysis, or behavioral-model based models (black-box), neural network analysis, fuzzy diagnosis, etc.. For example, Placca and Kouta [17] demonstrated a degradation process modeling of a PEMFC using fault tree analysis. In Ref. [18], a model-based condition monitoring that employs statistical analysis for fault detection of PEMFC is used. The instantaneous load current, the temperature and fuel/gas source pressure are measured and fed into a lumped parameter dynamic model for the establishment of a baseline for comparison. In Ref. [19], a NLAR (nonlinear analytical redundancy) technique is applied in a PEMFC system based on its mathematic model. Nonlinear analytical residuals are generated based on the elimination of the unknown variables of the system by an extended parity space approach to detect and isolate actuator and sensor faults. Other model-based fault detection methodologies

require linearization as in Ref. [20], where a dynamic model of the fuel cell as a part of a hybrid power system is built. The state space model is obtained by linearizing the dynamic model in operation points. The fault detection is based on checking the residuals between the signals monitored by a sensor and its estimation using the detection model at each sample point. While in Ref. [21], a flooding diagnosis procedure based on black-box model is used. Fault detection is based on the analysis of a residual obtained from the comparison between an experimental and an estimated pressure drop. The estimation is ensured by an artificial neural network that has been trained with flooding-free data. The main difficulty in model-based approaches lies in finding a global model capable of characterizing the dynamic and transient behavior of the fuel cell.

5. The Need of Energy Storage Devices

One of the solutions being proposed to improve the reliability and performance of renewable energy systems is to integrate energy storage devices into the power system network. Batteries used in power system applications so far are deep cycle batteries, similar to the ones used in electric vehicles, with energy capacity ranging from 17 MWh to 40 MWh and having efficiencies of about 70%-80%. The main energy storage technologies used for power systems are lead acids, flooded type and VRLA (valve-regulated lead acid) type, NaS (sodium sulphur), Li ion (lithium ion), metal air, and flow batteries such as regenerative fuel cell, VRB (vanadium redox) and ZnBr (Zinc Bromine) [22]. Amongst all these batteries, the lead-acid battery is the oldest and most mature technology used in a majority of power system applications. Table 1 shows some of the characteristics of these batteries. Specifically, valve-regulated lead acid batteries have been widely used in photovoltaic system, PV/wind hybrid energy conversion system, and standalone renewable power generation due to their low cost and wide availability [23]. Because the batteries can be over discharged, or operated under partial state of

Table 1 Operational characteristics of lead acid batteries.

	Flooded type	Valve regulated type
Efficiency	72%-78%	72%-78%
Life span	1,000-2,000 cycles at 70% DOD	200-300 cycles at 80% DOD
Operating temperature	-5 at 40 °C	-5 at 40 °C
Self discharge	2%-5%/month	2%-5%/month

charge, their service life in renewable power systems is shorter than could be expected. Batteries used in renewable energy systems can be overcharged, or over discharged depending on the condition of the renewable energy source available.

They often cycle in different state of charge and DOD (depth of discharge) than in other lead-acid battery applications.

6. Diagnosing the Degradation of Lead-Acid Batteries

There are several methods available for monitoring the conditions of batteries [24]. They can be characterized through the SOC (state-of-charge) which is a measure of the deliverable capacity of the battery with respect to its nominal capacity and the SOH (state-of-health) which indicates the ability of the battery to perform well during charging and discharging period. The following subsections review most of the methods developed for estimating the SOH of a battery unit.

6.1 Condition Monitoring Using Discharge Capacity

The discharge capacity is the most popular method for indicating the SOH of lead-acid battery. In this method, the battery life is defined to be stopped when the capacity is decreased to approximately 60%-80% of the initial value. The capacity method is based on counting discharging Coulomb to determine the SOH of a battery. Estimation using the Coulomb counter carries an average error of 15%.

6.2 Condition Monitoring Using Coup de Fouet

Lead-acid batteries have the characteristic of coup de fouet at the beginning of the discharge process. This

method involves measuring the trough voltage (low-voltage point) in the “coup de fouet” region appearing in the early minutes of the battery discharge. Aging of lead acid batteries causes a decrease in the deliverable capacity and also a lower coup de fouet voltage [25]. However, the coup de fouet phenomenon only occurs in batteries that are completely charged. Moreover, it only appears at the positive electrode and not at the negative electrode. Therefore, the coup de fouet method can not be used to determine the SOH of a battery in all conditions [26].

6.3 Condition Monitoring Using Internal Impedance

Kim and Hwang [27] measured the internal impedance of the battery as an indicator of its SOH. In general, the impedance and resistance of a lead acid battery increase with the battery age and the capacity lost. Analysis can be done in two ways, the DCR (direct current resistance) and the ACR (alternating current resistance). The fuzzy logic data analysis can also be incorporated with the impedance measurement to effectively estimate the SOH of the battery as done in Ref. [28]. Other algorithms are possible for measurement, many work was done using Kalman filter [29]. The accuracy of the impedance method for SOH estimation is restricted due to the difficulty of accurately measuring the small impedance. Besides, reliance on a single frequency point during impedance measurement can not provide information about all the processes that affect the health of a battery.

6.4 Condition Monitoring Using Conventional Discharge Test—Voltage Recovery

In this approach, a load is applied to the battery and the voltage depression under load and the temporal recovery of the battery voltage after removal of the load are monitored and used to estimate the SOH of the battery. Nevertheless, discharge methods require temporarily shutting-down of the system and the testing of individual cells which is time consuming and expensive and, is also detrimental to batteries, since

routine deep discharges can reduce the battery life.

6.5 Condition Monitoring Using Statistical Analysis

In Ref. [30], a new statistical approach known as ApEn (approximate entropy) is used. ApEn can be used to quantify irregularities of signals. Greater irregularities produce larger ApEn value. The SOH of a battery is determined by tracing abrupt changes in discharge voltage and discharge power at the end of every discharge cycle. For a healthy battery, the discharge voltage will be decreased to follow the reduction of capacity smoothly resulting in low ApEn. However, this technique can detect degradation due to internal shorts, opening of internal short or cell reversal but not due to grid corrosion and water loss [31].

6.6 Condition Monitoring Using Representative Approaches

These are model-based fault detection methods. They can be used to determine if a fault is present in the battery by making use of faults which can be modeled, typically through system identification. This type of fault detection and diagnosis is popular when a well-defined model of the battery can be created and utilized [32]. Model-based fault detection approaches include parity space-based approach, eigen-structure assignment-based approach, parameter identification-based approach and observer-based approach. In order to achieve accurate and robust battery diagnosis/prognosis more than one feature measurement of the battery need to be combined via an integrated algorithm. In general, model-based SOH monitoring methods consist of battery signals pre-processing, voltage estimation, residual generation and residual evaluation [33].

7. Conclusions

Solar energy, fuel cells and wind energy have experienced a remarkably rapid growth in the past 10 years because they are pollution-free power sources. Nevertheless, because different renewable energy

sources can complement each other, hybrid power sources as a combination of all three renewable energy sources can be used along with batteries. Yet, the structure of such hybrid sources is complex and vulnerable to faults. Therefore, it is necessary to investigate more in the fault detection and diagnosis of such hybrid systems to ensure effective normal power generation, rapid and accurate detection of fault location and prediction of fault occurrence. There are few works done on the diagnosis of hybrid renewable energy systems. In this paper, the authors presented a comprehensive review on the fault analysis of each of these renewable energy sources. After studying the fault detection and diagnosis of these renewable systems individually, future work will propose a valid technique applicable on the entire hybrid system.

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