Fault Detection and Diagnosis of Renewable Energy Systems: An Overview

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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 the service. In this paper, the authors are interested in presenting different methods of fault detection and diagnosis for industrial systems. Then, an overview of the diagnosis of wind turbine power generator, PV cell and PEM fuel cell is presented.**

Keywords-diagnosis; fault detection; renewable energy systems, wind turbine; PV cell; PEM fuel cell

I. Introduction

There has been an increasing interest in fault diagnosis in recent years, as a result of the growing demand for higher performance, efficient, reliability and safety especially for safety related processes like power plants and chemical plants and applying it on renewable energy systems is of no new work. Energy companies are investing in technologies to make better use of renewable energy sources such as wind, solar, fuel cell, biomass, and geothermal to generate electric power, where no power generation due to a fault is worse than the absence of the renewable energy source. Therefore fault detection techniques are becoming crucial in renewable energy systems. They offer prevention of components failure, reduction of maintenance cost, and detection of degradation. They also provide detailed information on the performance and operation of the systems, allow for condition based monitoring schemes and solve the problem of short lifetime of equipments arising with excessive maintenance [1]. In this paper, an overview of fault detection methods is discussed in Section 2. Section 3 presents diagnosis of wind turbine power generators. Fault detection of PV cell is treated in Section 4. Section 5 discusses the diagnosis of fuel cell. Finally, a conclusion about hybrid renewable energy systems is given in section 6.

II. Fault Detection and Diagnosis

Fault detection is an important process in process engineering [2]. It is the central component of abnormal event management (AEM) which is the task of responding to abnormal events in a process. This involves the timely detection of an abnormal event, diagnosing its causes and then taking appropriate control decisions and actions to bring the process back to normal, safe, operating state.

To start with the definition of fault, the term fault generally defines departure from an acceptable range of an observed variable to a calculated parameter associated with a process [3].

A. Classification of diagnostic systems

There is an 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. 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 [2]. For each of these methods, there exist several underlying techniques for fault diagnosis. There are two main components in classifying a diagnosis system:

- the type of a priori process knowledge,
- the type of diagnostic search technique.

The basic a priori knowledge that is needed for fault diagnosis is the set of failures and the relationship between the observations (symptoms) and the failures. The diagnostic search technique depends on the knowledge representation scheme which is greatly influenced by the kind o a priori knowledge available. Accordingly, a priori domain knowledge can be developed using process history-based knowledge or model-based a priori knowledge which can be classified as qualitative or quantitative. In quantitative models mathematical functional relationships between the input and outputs of the system are needed [4]. In qualitative models these relationships are expressed in terms of qualitative functions around different units in the process. In process history based models, only the availability of large amount of historical process data is assumed. Under the quantitative model based approaches, there exist techniques that use analytical redundancy to generate residuals that can be used for isolating process failures. For example, residual generation through diagnostic observers, parity relations, Kalman filters and so on [5]. Under the qualitative model based approaches, approaches like signed directed graph (SDG), fault trees, qualitative simulation (QSIM), and qualitative process theory (QPT) are used for fault diagnosis [6]. Under process history based approaches, both qualitative approaches such as expert systems and qualitative trend analysis (QTA) techniques and quantitative approaches such as neural networks, PCA and statistical classifiers are used [7].

B. *Desirable characteristics of a fault diagnostic system*

In order to compare various diagnostic approaches, a list of ten desirable characteristics that a diagnostic system should posses is proposed in [5]:

- Quick detection and diagnosis: the diagnostic system should respond quickly in detecting and diagnosing process malfunctions,
- Isolability: the ability of a diagnostic system to distinguish between different faults,
- Robustness: the ability of a diagnostic system to be robust to various noise and uncertainties,
- Novelty identifiability: the ability of a diagnostic system to distinguish novel, unknown faults from other known malfunctions or normal operation,
- Classification error estimate: the ability of a diagnostic system to provide a priori estimate on classification error that can occur,
- Adaptability: the ability of a diagnostic system to adapt to changes such as changes in production quantities with changing demands, changes in the quality of raw material, etc,
- Explanation facility: the ability of a diagnostic system to provide explanations on how the fault originated and propagated to the current situation,
- Modeling requirements: for fast and easy deployment, the modeling effort of a diagnostic system should be as minimal as possible,
- Storage and computational requirements: the ability of a diagnostic system to achieve a reasonable balance between computational complexity and storage requirements,
- Multiple fault identifiability: the ability to identify multiple faults, which is difficult due to the interacting nature of most faults.

C. *Methodes for fault detection*

The main purpose of fault detection is to generate a set of symptoms which indicate the difference between nominal and faulty status. The methods of fault detection can be divided into [8]:

- Signal threshold based approaches,
- Signal model based approaches,
- Process model based approaches.

D. *Methodes for fault isolation*

The main purpose of the fault isolation is to localize faults, to determine the time of detection and to identify the type, size and cause of faults with as many details as possible. The fault isolation procedure is based on the observed analytical and heuristic symptoms and the a-priori knowledge of the process. Isolability and novelty identifiability are essential for fault isolation. According to the a-priori process knowledge and the search techniques used, the approaches can be viewed as [8]:

- Classification approaches: If no further knowledge is available for the relations between features and faults, classification or pattern recognition approaches can be used, such as statistical, geometrical, neural networks, neuro-fuzzy networks, fuzzy clustering and support vector machines (SVMs).
- Inference approaches: Inference approaches can be applied to the fault isolation if causal relationships between faults and symptoms are known or partially known. Causal relationships may be represented by fault tree, fuzzy relations, expert system knowledge.

III. Fault Detection and Diagnosis of Wind Turbine Power Generators

Wind energy has been the fastest renewable energy source in terms of installation [9]. One important issue of wind energy is competitiveness when compared with other power plants, one exacerbated by the relatively high cost of operation and maintenance. The most efficient way of reducing these costs relies on condition monitoring and fault diagnosis of the wind turbine system.

A. *Basic Wind Energy Generator Topologies*

Wind energy systems are composed of three main types of wind generators [10]:

- Squirrel Cage Induction Generator (SCIG): SCIG is simple, reliable, cheap and lightweight, and the need of maintenance is very low. The machine is mechanically driven by a wind turbine through a gearbox which gives higher angular velocity of the electric machine. The slip, and hence the rotor speed varies with the amount of power generated. In spite of the presence of reactive power batteries, after a short circuit occurrence, all the reactive power needed by this kind of machines must be taken from the power network. This fact is one of the principal causes of out of service of this kind of machines. Nowadays they are being substituted by higher controllable generators, but they still are one of the most popular machines for wind power conversion. SCIG can run at two different, but constant, speeds by changing the number of pole pairs of the stator winding.
- Permanent Magnetic Synchronous Generators (PMSG): In the PMSG the rotor is magnetized by permanent magnets. The generator works at variable velocity and the maximum power is transferred to the grid through a CA-CCCA converter that keeps the generator frequency constant and equal to the grid frequency. The generator is directly connected to the wind turbine with no need of gearbox which gives a reduction on the weight, noise and in maintenance costs, but needs a higher number of poles to compensate the lower velocity of operation.
- Doubly Fed Induction Generators (DFIG): DFIG is most used due to the merits based low cost for inverter and the bidirectional power flow in wind power generation systems [11]. The advantage of these machines is that currents in the rotor winding can be controlled by the electrical converter, which gives the possibility of control the stator currents. In this way, the mechanical and electrical rotor frequencies are

decoupled and the electrical stator and rotor frequency can be matched, independently of the mechanical rotor speed.

B. Types of Faults

The wind turbine is a complex mechanical system. Faults can almost occur anywhere in this system and can be classified into:

- Electrical faults: These are the most unexpected because literally all used equipment and electrical machinery are well developed, tested and known. Such faults are transformer overheating, converter failure, stator winding short circuit, generator faults, etc.
- Electronic faults: They have a higher occurrence frequency than the electrical faults. These kinds of problems occur frequently in sensors and in electronic cards.
- Mechanical faults: These are mainly associated to the gearbox and the blades.

Some of these faults occurs more frequently than others and yield more serious shortcomings and thus is worth studying and researching [12].

C. Fault detection methodologies used in wind turbine generators

Many tools have been developed for fault detection in wind turbines. Most of them depend on the data collected from the installed sensors. The wind turbine has a lot of sensors that can be used to measure the vibration, temperature, speed, output power or generator current [13]. Such information form important measurements as input data for condition monitoring and fault detection in a wind turbine. For example, the power curve of a wind turbine shows how the turbine reacts to a specific wind speed. Thus, analyzing the wind speed and the power output and comparing the real power output with the expected one, the overall health of the turbine can be supervised. On the other hand, the analysis of the internal turbine components temperature associated to the power output curve can give an image of the health of the component. The problem is how to calculate the normal behavior expected for each of the monitored data types according to its current working and environmental conditions.

Measurements from the wind turbine are enormous and as such the use of neural network is beneficial. Reference [14] gives an example on the detection of failure in the electric generator of a wind turbine using a neural network. The neural network is trained using measured data from the wind turbine 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 wind turbine. Measurements are usually 10 minutes average values. By calculating the mean absolute error between the expected normal temperature and the real measured one, we can predict faults in the generator. Notice that once any small change occurs in the wind turbine, like replacing an equipment, we need to create a new model to the wind turbine; i.e., a new neural network needs to be trained.

Although thermal and vibration monitoring have been used for decades, most of the recent research has 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 reference [15], 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 wind turbine. Failure diagnosis based on frequency representations (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 the presence of faults like air-gap eccentricity, broken rotor bars and bearing damage. According to the authors and as compared to Periodogram and Welch Periodogram, the spectrogram and the scalogram, which are time-frequency representations, bring up major information concerning the time occurrence of the fault and exhibit a better signal-to-noise in the face of noise. In reference [11], FFT was used to detect inverter fault in the wind turbine. 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 faults.

Many of the methods used in condition monitoring and fault detection in wind turbines are inspired from electric motor condition monitoring. Accordingly, when researching in fault diagnosis of wind turbine systems one should study fault diagnosis of induction motors [16]. Many electrical and mechanical faults in induction motors have a direct impact on the motor magnetic field. Recently, it has been demonstrated that many failures lead to stator current modulation. Reference [17] focuses on the mechanical failures in wind turbines that lead to stator current amplitude modulation (AM). 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 generators. A comparison between the two transforms shows that, even if CT is computationally more attractive than HT, the latter can be used for balanced and unbalanced systems, stationary and non-stationary cases unlike CT which is only suitable for balanced systems.

IV. Fault Analysis of PV Arrays

PV power generation has been applied more and more widely owing to the many advantages of this renewable energy source such as free of pollution, safe, without noise, general resource, easy to install, and short construction period. In theory, the solar cell modules have the life span of about 20 years, but in practice, due to several reasons, some modules are damaged after being used for 8-10 years. Therefore, in order 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.

A. Operation and Configuration of PV Cell

The solar cell is the key component which enables the conversion of solar energy into electrical energy. A typical model of a solar cell contains a solar-based current source, a diode, a quite large parallel resistance, and a very small series resistance. The series resistance is an equivalent value of the body resistance and surface resistance of the solar cell in addition to electrode conductor resistance and metal electrode resistance. The parallel resistance is an equivalent value of the leaking resistance of PN-junction caused by pollution on the cell surface and defect of semiconductor. The output of current source keeps direct proportion to light intensity. The voltage and current of diode obey the normal PN diode characteristic curve.

Accordingly, the output characteristics curve of a PV cell presents a transition from constant current output state to constant voltage output state with voltage increases, and there is a maximum power point at the boundary of these two states. Generally, the PV array works in this maximum power point with the MPPT (Maximum Power Point Tracking) function, where modern inverters are used to dynamically adjust the load they present to the array in order to maintain operation at the MPP.

In a solar PV generation system, the output voltage of a PV cell is only 0.5V because of the limitation of the process, the PV module is constructed by connecting several PV cells in series, and the PV array is formed by several PV modules in series-parallel connection in order to satisfy the high-voltage high-power supply requirements. Normally, there are 36 cells in a PV module connected in series-parallel mode. A power plant consists of solar cell arrays, MPPT controllers, energy storage units, and inverters.

B. Different PV connections

Solar cells can be connected in several different ways. The main connections are the series connection, parallel connection, series-parallel connection, parallel-series connection, also known as total-cross-tied array, and some other proposed modifications of these [18]. In series connection, the PV cells are connected in series. The output voltage is equal to the sum of the voltages of all cells and the output current is the current in each of the cells. When one cell is shaded, it directly affects the power delivered by other cells. In parallel connection, the PV cells are connected in parallel. The output current is equal to the sum of currents of all cells and the output voltage is the voltage in each of the cells. It is the most robust configuration under shadow conditions; however, the output voltage of 0.5V is too low to store and generate electricity. In series-parallel array, all PV cells are connected in series forming strings. Then, strings are connected in parallel. Its shortcomings are similar to series connections. In parallel-series array, PV cells are connected in parallel creating modules. Then, those modules are connected in series. When some cells are shaded, other PV cells connected in series are not affected.

C. Types of faults in PV systems

The failure of PV arrays is mainly divided into:

- Degradation of modules: Module aging can occurs when the series resistance increases, when the shunt resistance decreases, or possibly when the film of reducing the reflection degenerates.
- Short circuit in cell or module: Cell short circuit is easy to occur in the thin-film batteries as the pinhole, localized corrosion and battery material damage. On the other hand, module short circuit is usually the result of manufacturing defects.
- Open circuit in cell or module: Cell open circuit is mostly caused by fragmentation of cells; however, module open circuit occurs when a line is disconnected.
- Hot-spot (shadowing): Hot spot is one of the main problems of arrays of PV cells. It results from long shade of part of the PC cells. In the occasion of the shadowing, the output current of the branch with blocked cells significantly decreases because of the current dissipation of the fault module. They produce negative voltage and thus act as the load of the circuit and even consume power from other normal PV cells. It is well recognized that connecting the PV cells in parallel opposed bypass diodes can avoid Hot Spot. However, this requires a number of cell monomers and presents power loss of PV arrays associated with the current passed through bypass diodes. At present detecting Hot Spot is commonly based on the infrared image analysis. Nevertheless, this method suffers from several shortcomings, such as its inferior sensitivity in the minor temperature differences, poor real-timeliness, hamstrung malfunction analysis and alarm online, low accuracy and efficiency.

D. Fault detection methods for PV systems

Among the fault detection methods used in PV arrays are:

- Output I-V measurement: Many proposals exist on the rearrangement of the connection of PV cells along with efficient installation of voltage and current sensors. These sensors are used to detect and localize faults in PV arrays using current-voltage measured data by comparing it with nominal rated data. [18]. Collecting current and voltage measurements at different points of the PV array can approximate the location of the faulted cell module; however, it cannot locate precisely the fault position and distinguish the type of fault. For example in reference [19], sensors were arranged in a way such that the fault branch can be detected by the significant decrease in its output current and the concrete fault point of that branch can be located according to voltage analysis. Usually when the output current is zero, an open-circuit fault can be confirmed. A current drop less than 10% of the rated current doesn't necessarily indicate a fault. A decrease between 10% to 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 current, hot spot can be determined [19]. Another paper [20] presents a statistical analysis of the output current and voltage to detect faulty modules by clustering strategy and outlier values.
- Infrared image analysis: Under the same sunshine, ambient temperature, different working conditions (normal, shading, failure, aging), and different load conditions (rated load, no load, short circuit), the absorption, conversion and output of PV cell energy are different, so the temperature characteristics are not the same. Infrared image can reflect these characteristics of temperature difference. Thus, the

surface temperature of PV cells with fault differs from that of normal working PV cells, leading to an obvious difference between the two infrared images. The main disadvantage is the need of an infrared imaging device. Another disadvantage is the impact of several environmental factors (other than faults) on the PV cell temperature and infrared properties.

- Maximum power point tracking: A time tracking method 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 faults.
- New strategies: Papers [21] proposes a model-based fault diagnosis method of PV arrays. In [22] artificial neural network analysis was used. Reference [23] employs fuzzy control theory in PV systems and [24] utilizes electrical fault diagnosis methods such as the earth capacitance measurement (ECM) and the time domain reflectometry (TDR). Fuzzy concept characterization gives a calculation criterion that detects the difference between measured module current and expected current to alarm for a fault. Whereas ECM can locate the disconnection between modules by comparing the earth capacitances of normal string and faulty string for completion inspection or at the accidents. On the other hand, TDR is the electrical method that measures the electrical characteristic of transmission lines and detects the breakdown point. It is one of the RF measurements similar to the radar. In TDR, the applied signal into the line and the reflected signal caused by the impedance mismatches in the line are compared. The signal delay and the change of waveform are translated into fault position in the line and the fault type.

V. Fault Detection of PEM Fuel Cell

Polymer electrolyte membrane (PEM) fuel cells are energy systems that convert directly the chemical energy of hydrogen into electrical energy with high efficiency without CO_2 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 PEM fuel cells systems, 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.

A single fuel cell is mainly composed of a membrane, catalyst layers (anode and cathode electrodes) and diffusion layers (anode and cathode electrodes). Due to the complexity of the physical process and the functional limitations of these components, faults conditions and even failure may occur under practical operating conditions.

A. Types of Faults in Fuel Cells

Faults can be mainly classified into: degradation due to aging or degradation due to operation incidents such as dehydration and drying of the membrane, the fuel/gas of the electrochemical reaction (due to channel flow variation or flooding), and the leak of the membrane. All fault incidents have a common consequence which is a voltage drop.

- Dehydration and drying of the membrane: The electrolyte membrane needs to be appropriately hydrated in order to efficiently conduct the hydrogen protons and prevent the occurrence of localized hot spots. The dehydration and drying of the membrane lead to the increase of the internal resistance and a larger output voltage loss, which in turn raises the local temperature of the membrane causing hot spots that eventually damage the membrane. This phenomenon usually occurs at the anode side.
- Fuel/gas starvation: The first stage may be caused by the channel flow variation within the stack, i.e., the flow resistance directly resulting in the fuel/gas starvation in the channels, and consequently the electrolyte fuel/gas starvation. The reasons include the liquid water droplets forming in the flow channels, the temperature variation, and geometry deviation. The second stage fuel/gas starvation may be caused by the electrode pores blocked by the liquid water, which is termed "flooding". This phenomenon generally occurs at the cathode side. The fuel/gas starvation may interrupt the electrochemical reaction and lead to rapid loss in the output voltage. It may even lead to decomposition of the fuel cell components and damage the cell [25].
- Leak of membrane: This is due to the fracture and/or hole of the membrane. While the holes in the membrane may be caused by hot spot, the fracture results from mechanical stress concentration. Under dynamic operating conditions, the pressure difference across the membrane-electrode assembly (MEA) may break the membrane.

B. Fault detection methods of PEM fuel cell systems

In order to improve the reliability and overall performance of PEM fuel cell systems, a number of design and control strategies have been proposed. Fuel cell diagnosis can be considered under different approaches, going from heuristic knowledge to mathematical models [25], such as mechanistic model-based diagnosis, residual analysis, or behavioral-model based models (black-box), neutral network analysis, fuzzy diagnosis, etc. For example, in [26] degradations process modeling of a PEM fuel cell using fault tree analysis is demonstrated. In [27] a model-based condition monitoring that employs statistical analysis for fault detection of PEM fuel cells 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 [28] a nonlinear analytical redundancy (NLAR) technique is applied in a PEM fuel cell system based on its mathematic model. The proposed model is simplified into a five orders state space representation. 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 [29], 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 [30] a flooding diagnosis procedure based on black-box model is used. This procedure 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. Fault detection is obtained by means of a residual analysis.

The main difficulty in the online monitoring for PEM fuel cells stems from the system complexity. A fuel cell system normally operates under dynamic and varying conditions, like constant changes in load current, temperature, flow rate, etc. Thus a dynamic model of PEM fuel cell that characterizes the complicated interactions of the temperature, gas flow, phase change in the anode and cathode channels, and membrane humidification under operating conditions is necessary. While over the years PEM fuel cells have been modeled at various levels, a global model capable of characterizing the dynamic and transient behavior of the fuel cells is still being pursued.

VI. CONCLUSION

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. Moreover, they generate power near the load centers, which eliminates the need to run high voltage transmission lines. Nevertheless, because different renewable energy sources can complement each other, multi-source hybrid alternative energy systems have great potential to provide higher quality and more reliable power to customers than a system based on a single resource. These renewable energy systems can either be standalone or grid-connected. For a standalone application, the system needs to have sufficient storage capacity to handle power variations from the involved alternative energy sources. Such system can be considered as a micro-grid. For a grid-connected mode, the alternative energy sources in the micro-grid can supply power both to local loads and to the utility grid. Hybrid power sources as a combination of all three renewable energy sources or maybe as a combination of only two of them can be used possibly along with batteries. But 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.

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