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Fault diagnostics in smart micro-grids: A survey

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ABSTRACT

Due to rising awareness on environmental protection and for maintenance of clean habitable communities, current and next generation micro-grids are desired to have significant penetration of renewable and clean energy sources. However, a critical issue is the growth of faults in various components of micro-grids, which comprise the underlying energy generation and distribution infrastructure. Moreover, faults can manifest through different failure modes in the same component. If timely diagnostics and maintenance actions are not undertaken, then these faults can cause instabilities, inefficient power generation, and other losses. Therefore, it is important not only to understand the various failure modes, and their root causes and effects, but also to develop real-time automated diagnostics tools that can capture the early signatures of fault evolution for mitigating actions.

In this respect, this paper presents a review of different failure modes occurring in various micro-grid components including both clean and conventional energy generation systems. Subsequently, the paper also provides a review on the state-of-the-art of various fault diagnosis approaches available in technical literature. Since multiple approaches can be implemented utilizing the model-based or data-driven methods given the system monitoring and communication infrastructures, the paper has presented the material in a systematic manner for easy understanding. The information presented in this paper will benefit not only the diagnostic engineers but also the control engineers who aim to develop control methodologies for fault-tolerance, mitigation, and equipment life extension based on the tools of early diagnostics.

Contents

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1. Introduction

With rapid growth of sensing, control and communication technologies in the last few decades, the power systems community has witnessed the emergence of *smart micro-grids* [1,2] as a viable solution to respond to the emergency situations of the main grid. A smart micro-grid [3,4] is a self-contained distributed power system that allows for high system-level energy sustainability, reliability, availability, and load support. Typically, the energy infrastructure of a micro-grid can have clean energy penetration even up to the consumer level to maintain sustainable performance. Under critical circumstances or emergency situations when the main grid is unable to meet the demand due to catastrophic failures or instabilities, a micro-grid can utilize clean as well as conventional systems for continual and reliable power generation. During the regular operation period, the micro-grids enable load sharing with the main grid for efficient performance.

In general, the energy infrastructure of a micro-grid can vary depending on the geographical conditions, availability of the type of generation systems, and socio-economics such as acceptability, availability, and accessibility. For example, micro-grids can be developed with no renewable energy resources in regions where renewable energy cannot be harvested, while the micro-grids in regions with abundance of sun light can be primarily built upon the Solar Photovoltaic renewable energy. However, due to rising awareness on environmental protection and for maintenance of clean habitable communities, current and next generation micro-grids are desired to have significant penetration of renewable and clean energy sources.

Faults and failures can occur in the main grid or the micro-grid without early warnings due to a variety of possible causes including but not limited to equipment failures, falling of trees on electrical lines, lightning strikes, animal/tree contacts, and malicious attacks [5]. When a fault occurs in a certain region of a traditional power system, some other regions of the grid may become overloaded or isolated through tipped switchgear due to load redistribution [6,7]. This continuous load redistribution often turns into a cascading phenomenon that is propagated throughout the power system that in turn can cause a catastrophic failure leading to large power disruptions and huge social and economic impacts on society [8,9]. For example, this phenomenon occurred in August 2003 when significant portions of Northeastern US and Ontario, Canada, experienced a cascading failure leading to large power blackout, thus lending $\sim$50 million people without power and causing an estimated loss of $\sim$\$4 to \$10 billion [10].

To circumvent this phenomenon, smart micro-grids are typically designed to disconnect energy supply from the main grid and shift into a self-contained island mode to mitigate the effects of cascading failures, while maintaining power using clean and/or conventional technologies and by storing it using energy storage devices. But even in the island mode, a micro-grid is itself subject to faults. Since micro-grids are being implemented and installed world-wide [1], a thorough study is necessary to understand the failure modes of the various components of the clean and conventional energy generation infrastructure of the micro-grids and the causes and effects of these failures. It is also useful to review the technical literature for the state-of-the-art methods used for diagnosis of these faults.

Technical literature reports several fault diagnosis methods that consist of primarily model-based and data-driven methods. Model-based methods rely on experimentally verified models of the physical system, which can accurately represent the nominal operating condition and also the effects of failure modes. In the case when real data is not available, these models could be utilized to generate time-series data for the healthy system and under faulty scenarios, wherein fault diagnosis algorithms and probabilistic tests could be developed to diagnose the system's health. On the other hand, purely data-driven methods rely on the real data measured from the physical system, which can be used to train fault diagnosis algorithms as needed.

This paper provides a review of the current methods of fault diagnosis in micro-grids with significant clean energy penetration. This review extends the authors' prior work [11] from a basic overview of faults in the micro-grid components to include: methods used to recognize any significant changes in the main grid performance, a discussion of the micro-grids' electrical infrastructure, detailed description of component failure modes with a focus on clean and conventional systems, construction of a Failure modes, Causes and Effects Table, and systematic representation of various diagnostic methods to identify faults based on the monitoring techniques and information available to the user. Several papers in literature have discussed the futuristic aspects, challenges, control aspects, and distributed generation systems in smart micro-grids [4], [12–18], however they lack a detailed discussion of the clean/conventional energy sources' failure modes and the state-of-the-art diagnostic methods. This paper could also provide useful information to control engineers who aim to develop intelligent reconfiguration control schemes for fault mitigation and equipment life extension via utilizing the tools of early diagnostics to enhance the reliability, resiliency and availability of next generation micro-grids.

The main contributions of this paper are as follows:

- Description of the micro-grid infrastructure including various monitoring devices and system configurations,
- Construction of a Failure modes, Causes, and Effects Table that provides the readers an easy access in understanding the various categories of faults in micro-grid components,
- A systematic representation of the diagnostics approaches based on the information available to the reader, and
- A review of state-of-the-art methods of fault diagnosis for various components of a micro-grid.

This paper is organized in the following structure. Section 2 describes a smart micro-grid, its electrical energy infrastructure, current monitoring methods, and configuration modes of operation. Section 3 discusses the faults within the various components of a micro-grid while Section 4 presents a study of the state-of-the-art diagnosis methods. Section 5 summarizes the paper via discussing the possibilities of future work needed to improve the existing diagnostic methods of micro-grids.

2. Micro-grid energy infrastructure

2.1. System description

Fig. 1 shows an essential feature of smart micro-grids, which is the integration of sensing, control and communication technologies with the distributed power generation system to form an efficient and reliable micro power system capable of delivering power even

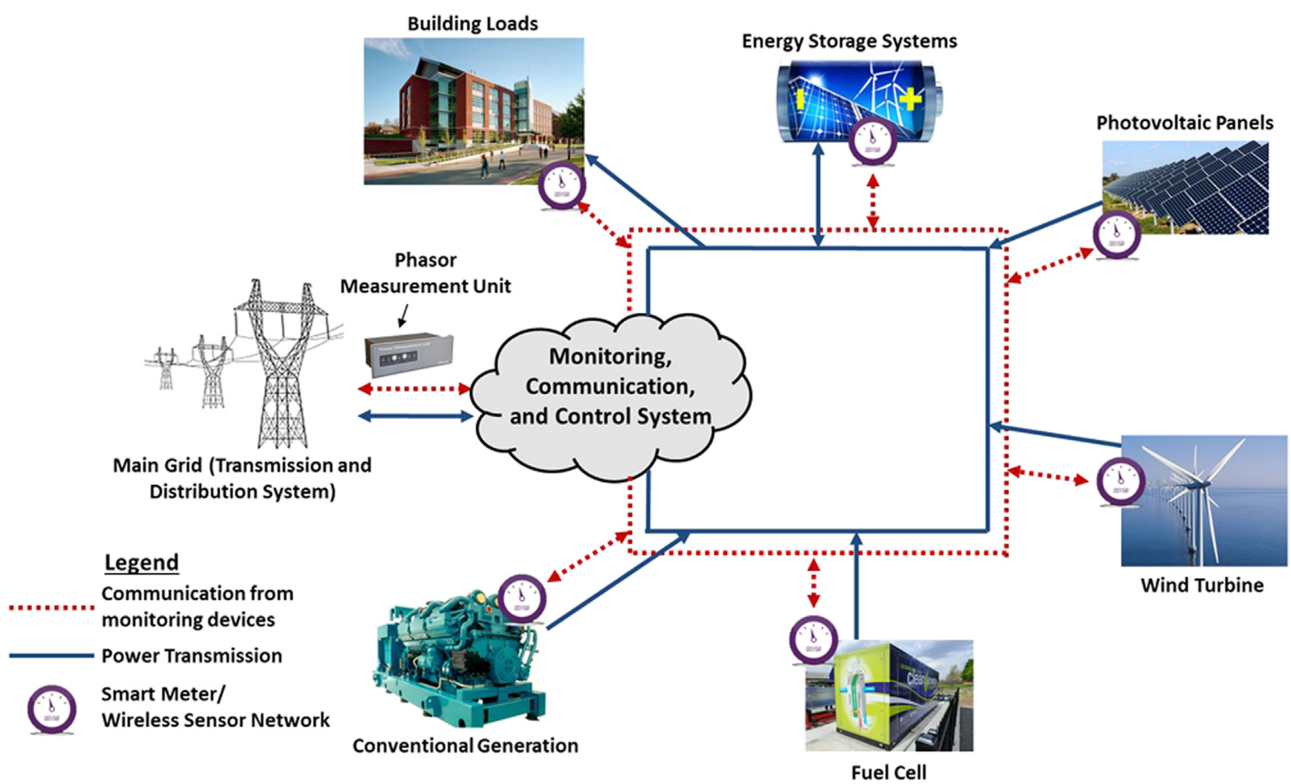

Fig. 1. Smart micro-grid energy generation and distribution infrastructure.

in the event of faults in the main utility grid. Micro-grids are configured as either dc or ac grids connected to low or medium voltage distribution networks [19]. They provide the attractive property of forming a distributed power system with significant utilization of clean energy sources for load support and sustainability. Typical clean energy sources include wind turbines, photovoltaic (PV) panels, and fuel cells. On the other hand, conventional generation systems, e.g. diesel or natural gas generators, are also used when clean energy sources cannot provide sufficient power to the micro-grid. All distributed generation systems require power electronic converters to connect to building loads or the utility grid. Their infrastructure is mainly interconnected through cables and possibly distribution-level transmission lines forming a unified power system for local load support. This study primarily focuses on the micro-grid's electrical energy infrastructure including both clean and conventional energy generation systems. Further study is needed to discuss faults and diagnostic technologies that cover a broad spectrum of distributed energy generation systems in addition to the energy storage devices.

2.2. Monitoring devices

A typical power system is equipped with several sensing devices that are installed at various locations to monitor the signals and states of different components of the energy infrastructure in a distributed fashion. These sensing devices detect sudden or gradual changes in voltage and current signals at various places to find any anomalies that deviate from the nominal condition. Examples of such devices include Smart Meters [20,21], Wireless Sensor Networks (WSNs) [22] and Phasor Measurement Units (PMUs) [23].

Smart Meters allow for observations of the energy consumption of the loads in the micro-grid while permitting communication in two directions, from the providers to the consumers and vice versa allowing for load control. Another method of capturing fault characteristics is utilizing WSNs to monitor the components of the generation systems or transmission lines. For example, WSNs may include a set of heterogeneous sensors, such as temperature, vibration, strain, actuator positions, cameras, etc. [24]. PMUs are utilized to measure the phase angles of the bus voltages of the main grid. This device is used to measure the current and voltage values which can help in recognizing any critical changes in the main utility grid, thus allowing the micro-grid to transition into island mode if necessary.

By including heterogeneous sensors throughout the micro-grid, many fault detection and isolation methods can be developed to provide early indication of faults in the micro-grid infrastructure. For example, vibration or strain sensors could be installed along the transmission lines to monitor if unhealthy loads are passing through the lines. Unhealthy loads can lead to phase-to-ground faults and blackouts to any loads connected to the lines. The monitoring devices implemented in the micro-grid could be even adapted to the diagnostic methods the user is planning to implement. Many different technologies may lead to unique information and features about the component faults.

Sensor measurements are communicated to a monitoring station via wireless or wired transmission protocols [25–27] which may include cellular networks, ZigBee, wireless mesh, and power line communication. Thus a seamless integration of sensing, communication and intelligent diagnostic methods for micro-grids instabilities and/or faults can be used to develop a stable and reliable power system.

2.3. Micro-grid configurations

Micro-grids operate under two configurations: (1) grid-connected and (2) island mode. Grid-connected mode provides voltage and power support locally and allows for reduction in line losses leading to an efficient use of power [22]. Island mode allows the micro-grid to disconnect from the utility grid and operate as an isolated power system, typically when there is a fault on the main grid or other emergency situation. The faults on the grid-side faults can be broadly grouped into: (1) balanced and (2) unbalanced faults [28]. These faults consist of even or unbalanced voltage drops respectively throughout each phase, leading to a tripped breaker forcing the micro-grid into island mode. If the breaker is tripped without protective measures, inverters within the micro-grid may witness voltage and/or current transients that cause semiconductor device faults [29].

To detect faults on the main grid side, voltage and current phasors at the point-of-common-coupling (PCC) are used and compared with their nominal values. For example, the authors in [29] utilize three-phase line currents and voltage measurements and compared them to their nominal value to generate residues, and introduced series inverters to respond to exceeded thresholds to protect the micro-grid's semiconductor devices. A similar method is used by Vasquez et al. [30] where grid parameters (frequency, voltage, and grid impedances) are compared with designed thresholds to trigger the micro-grid into island mode. By monitoring the frequency changes vs changes in the load power variations, Pai and Huang [31] identified a method to detect the islanding process. Once the main grid faults are cleared, the micro-grid again reconnects to the main grid.

3. Failure modes, causes and effects

Micro-grids are usually monitored using smart meters and non-invasive sensing devices for diagnosing faults to maintain stability and performance in island mode. Faults in the electrical infrastructure of the micro-grid become more problematic in island mode as every source, cable, or transmission line becomes more critical at the smaller micro-grid scale. Before providing a review of the diagnostic methods available throughout the literature, it is necessary to provide a detailed description of the fault universe of the various components of the micro-grid and also the causes and effects of the faults. The following subsections provide the details of these failure modes for various subsystems and components of a micro-grid while Table 1 summarizes them.

3.1. Cables and transmission lines

Power cables form the critical links between the generation sources and the loads of a micro-grid, but distribution-level transmission lines may also be used. They typically carry low voltage which is stepped down from the transmission grid or generated from the distributed generation systems. Power cables are usually installed underground while transmission lines are laid overhead.

Underground cables are subjected to mechanical faults, thermal runaway due to the compacted soil acting as an insulator, and usual wear and tear. Overhead lines on the other hand are prone to the natural causes that can cause faults due to lighting strikes, icing, breakage as a result of animal or tree interferences, short circuits, overloading, aging, human actions, or simply lack of maintenance [32,33]. The main transmission line faults that typically occur include the following:

- *Single Line-to-Ground Fault*: This fault occurs when one of the three phases physically connects with the ground causing a short circuit.
- *Double Line-to-Ground Fault*: This fault is similar in effect to the single line-to-ground except that in this case two of the three phases come in physical contact with the ground causing short circuits.
- *Line-to-Line Fault*: This fault occurs when a combination of two out of the three phases connect together causing a short circuit between them. This is typically caused when the cable insulation degrades and breaks resulting in open exposed wires.

3.2. Renewable energy systems

The failure modes of different renewable energy systems used in micro-grids are described below:

3.2.1. Photovoltaic (PV) panels

PV panels utilize solar radiation to generate power for the micro-grid. Their construction consists of materials such as glass, metals, polymers and semiconductors. Typical faults that occur in PV panels include the following:

- *Cell faults*: These faults can be further categorized into three main faults: (i) open/short circuited cells, (ii) hot-spot faults, and (iii) degradation faults. Open/short circuited cells are caused when a cell disconnects or shorts resulting in a loss of the cell. Hot-spot faults are caused when the panel is partially shaded or damaged which results in a decrease in the cell current. Degradation faults are caused when the cell series resistance increases due to over exposer, a decrease in cell shunt resistance due to crystal damage/impurities in the inter junction, debris accumulation on the surface, mismatched cells [34], and/or overheating.
- *Module faults*: these faults typically consist of open or short circuits, fractured glass, and delamination. Most of the time, these faults occur because of manufacturing defects, mechanical loads (such as snow accumulation), corrosion, natural occurrences, and degradation of the anti-reflection coating of the cells [35].
- *By-Pass diode faults*: these faults happen either due to a short or open circuit. If an open circuit fault occurs, the cell may be subjected to hot spots while short circuit faults will result in decreased generation efficiency. These typically occur due to an overheated diode.

The failure modes described above corresponding to the PV panels result in decreased output power leading to reduced voltage and current signals in the micro-grid.

3.2.2. Wind turbines

Wind turbines form another renewable energy resource that generate power from the wind. The turbines are subject to various faults in the following subsystems [36–38]:

- *Gearbox*: faults occurring in the gearbox are usually bearing faults which are the major cause of wind turbine failures [39] since they are in multiple subsystems. Bearing faults typically fall under two categories: inner/outer race faults or ball faults, which occur from abrasive wear, corrosion, lack of lubrication, and accumulation of debris [40].
- *Generator*: the generators can fail because of faults in the bearings, stator, and rotor. Bearing faults described above are similar. Stator and rotor faults are mainly open/short circuits, abnormal connections in windings, broken rotor bar, air eccentricity, and demagnetization. Stator faults appear because of insulation degradation which result in inter-turn short circuits [41], while rotor faults occur from broken or shorted windings [42]. Faults in the generator produce unbalanced voltages and currents, decreased average torque, excessive heating, and low generation efficiency [37,43].
- *Power electronics and electric control*: faults here primarily occur within the semiconductor devices and include short or open

Table 1
Fault universe of the various components in a micro-grids' electrical infrastructure.

Components	Sub-component	Failure mode	Cause	Effect
Cables and transmission lines		• Single line-to-ground • Double line-to-ground • Line-to-line	• Physical contact between one/two phases with ground/animal/tree • Broken insulators • Natural events e.g. lightning strikes • Overloading	• Introduces fault currents leading to tripped breaker, shutting off power flow
PV panel	Cell	• Degradation • Short/open-circuited cells • Interconnect open-circuits • Hot-spots	• Over exposer • Decrease in cell shunt resistance • Debris accumulation on the surface • Mismatched cells • Overheating	• Loss/reduction of output power • Decrease in voltage and current waveforms
	Module	• Open/short-circuits • Short-circuits • Fractured glass • Delamination	• Manufacturing defects, mechanical loads, corrosion • Natural occurrences • Degradation of cells anti-reflection coating	
	By-pass diode	• Open/short-circuit	• Overheating	
Wind turbine	Gearbox	• Bearing-Inner/outer race and ball faults	• Corrosion and contamination	• Unbalanced voltage and current waveforms
	Generator	• Bearing (See above) • Stator inter-turn short circuit • Cracked rotor • Air-gaps • Demagnetization	• Corrosion, contamination, manufacturing defects • Overheating • Reduction of fluid • Insulation damage	• Reduction in efficiency • Decreased torque • Phase shift • Increased vibration
	Power electronics and electric control	• Semiconductor short/open circuit	• Over voltage of components • Manufacturing defects	
	Blades	• Degradation	• Corrosion • Change in stiffness	
	Hydraulic control	• Fuel leak	• Air contamination and mechanical defects	
Fuel cell	Membrane, Electrocatalyst, Catalyst, and Gas Diffusion Layers	• Mechanical degradation • Thermal degradation • Chemical degradation	• Perforations, cracks, tears, or pinholes • Humidity cycling • Flooding/drying	• Reduction in efficiency • Loss of output power • Decrease in voltage and current waveforms
	Bipolar plate	• Loss of conductivity	• Corrosion	
	Sealing gasket	• Mechanical failure		
	Compressor Motor	• Degradation • Locked	• Increased friction • Overheating	
Conventional generation systems (e.g. diesel generator and engine)	Stator and Rotor	• Single/multi-phase short circuit • Inter-turn short circuit • Air-gaps • Grounding • Bending/broken rotor • Demagnetization	• Insulation damage leading to winding interconnections • Reduction of lubrication • Manufacturing defects • Overheating	• Phase shift • Unbalanced voltage and current waveforms • Reduction in efficiency
	Fuel line	• Leaking	• Holes/air contamination	• Decreased gas pressure and combustion efficiency
	Bearings	• Inner race • Outer race • Ball	• Vibration, High speeds • Wear, mechanical loads, and contamination • Electric arcing • Lack of lubrication • Misalignment	• Increased vibration • Decreased efficiency
	Crankshaft	• Cracked crankshaft	• Fatigue • Corrosion • Manufacture defects	

circuits and gate drive circuit faults which are typically caused by manufacturing defects, over-voltage stress, or over current and shoot-through conditions.

- *Blades*: the blades are susceptible to degradations from corrosion, mechanical damages, and manufacturing defects. Mechanical damages may be produce from ice, lightning, insects, etc. and can cause small defects on the blades' surface. This results in a loss in efficiency because of the change in blade stiffness.
- *Hydraulic control*: the main hydraulic control fault is fuel leaks which result from air contamination. This results in a loss of lubrication and eventually causes faults in the rotor, blades, and bearings.

Further details on the failure modes of Wind Turbines can be found in [44].

3.2.3. Fuel cells

One of the most common type of fuel cells are the Proton Exchange Membrane (PEM) fuel cells, which generate renewable power from the chemical energy discharge from the hydrogen and oxygen reaction. Their construction consists of the membrane, electro-catalyst, catalyst, and gas diffusion layers which tend to degrade over time [45]. The following degradations occur in these layers:

- *Mechanical degradations*: These are caused by perforations because of incorrect membrane electrode construction and/or humidity cycling.
- *Thermal degradations*: these are typically caused by a change in hydrations in the PEM, either due to flooding or dehydration [46,47]. This usually occurs when the fuel cell is operating at temperatures outside of the recommended operating range.
- *Chemical degradations*: These occur due to the combustion of hydrogen and oxygen. When they combust, foreign cationic ions may form causing the layers to degrade.

PEM fuel cells also contain three other components that suffer from degradations as well. These are the bipolar plate, sealing gasket, and compressor motor. The degradations for these components are described as follows:

- *Bipolar plate degradation*: this is caused by corrosion of the bipolar plate which slowly reduces the output voltage of the fuel cell.
- *Sealing gasket degradation*: this fault results from a decrease in the force retention of the sealing gasket. This causes compression loss which eventually leads to a bad seal causing electrical shorting of the plate.
- *Compressor motor degradation*: a degradation of compressor motor causes lock up resulting in a reduced or loss of air flow through the cell [48]. These typically occur due to increased friction and/or overheating of the compressor motor.

In general, fuel cell faults lead to decreased generation efficiency, and reduction/ loss of output power.

3.3. Conventional energy systems

Conventional generation systems are used to back-up renewable power generation. This paper considers diesel generators as the conventional energy systems; however, as environmental concerns grow throughout the world, natural gas may be substituted. Diesel generators are currently used to back-up renewable energy generation. Minimal research has been published on the faults for diesel generators; however the engine and electric generator faults have been reported. Diesel engines have the following faults:

- *Fuel leakage*: this occurs from the growth of small holes in the system and causes air contamination. This results in a decrease in gas pressure which further leads to a reduced combustion efficiency [52].
- *Bearing faults*: these faults are the same as those described in the Wind Turbine, Gearbox section. They are classified as inner/outer race and ball faults which are caused by increased mechanical loads, wear, and etching [40].
- *Crankshaft faults*: [49] the main fault for a crankshaft is the initiation and growth of cracks. This is caused because of corrosion or poor assembly and may lead to a reduced ability to generate rotational energy [50,51]. As cracks grow, the effects of the fault increase until the shaft breaks in half.

The electric generator faults are described below:

- *Stator and rotor faults*: the faults for these components are single/multiple phase short circuits, inter-turn short circuits [53,54], saturation, grounded windings, rotor bending/cracking, air eccentricity [55], and permanent magnet degradations [56]. These occur because of insulation damages/degradation, a reduction in lubrication, manufacturing defects, and overheating and lead to unbalanced voltages and current harmonics, a reduction in generation efficiency and current phase shifts [57].

The faults associated with diesel generators cause a decrease in their performance which can be observed as current and voltage drops.

The various failure modes of different micro-grid components as presented in this section provide an understanding of the fault universe. The next section provides a description of different fault diagnosis methods found in technical literature.

4. Fault diagnostics

Technical literature abounds with several fault diagnosis methods applied to the different components of a micro-grid. These methods primarily fall under two categories: (i) model-based and (ii) data-driven approaches. Model-based approaches for fault diagnosis require a detailed understanding of how the component functions. Typically these methods build and design tests that can detect and diagnose faults based on the models of the system rather than pure experimental/real-time data. Sometimes data from the real system is analyzed and compared with the outputs of a model of the healthy system to identify the system's health. On the other hand, purely data-driven approaches for fault diagnosis perform analysis on the experimental data measured from the real physical system. Both the model based and data-driven methods are illustrated in Fig. 2.

Fig. 3 shows the methods discussed throughout this study to identify faults in different components of a micro-grid. These methods are described as follows:

4.1. Theshold-based methods

Many methods reported in technical literature are based on identifying characteristics in faulty signals that allow for separation between healthy and faulty data. A simple method is to design thresholds or confidence bounds that capture the healthy dynamics of the system. When measurements exceed these thresholds or fall outside the confidence bounds, an event is triggered and the fault is detected.

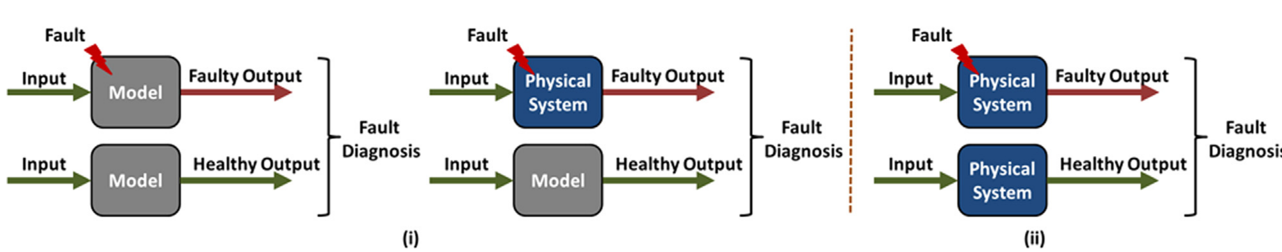

Fig. 2. (i) Model-based vs (ii) Data-driven methods for fault diagnosis.

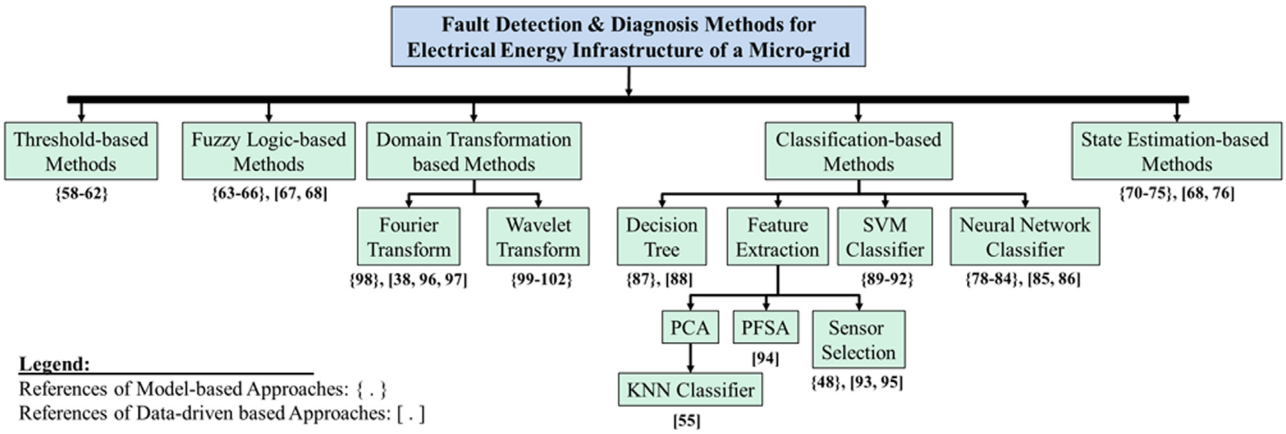

Fig. 3. Fault detection and diagnosis methods for micro-grids.

Model-based approaches that use threshold-based methods simulate detailed models of micro-grid components to generate data sets of critical system parameters for both healthy and faulty conditions. Subsequently, thresholds are designed by identifying confidence bounds for each critical system parameter. Then, threshold-based tests are developed to detect a fault if a signal falls outside of these bounds. For example, threshold-based tests have been employed for detection of module faults in PV panels by comparing the loss of power loss between real and simulated data [58]. Ndiaye et al. [59] identified module degradation in PV panels through a comparison of parameters such as short-circuit current, open-circuit voltage, and maximum output power with their simulated references, respectively. These methods have also been applied for module fault isolation [60] and hot spot faults [61]. Sometimes the thresholds are made adaptive to operating conditions such as in the study by Ingimundarson et al. [62] of fuel cells, which calculated the rate of change in anode pressure and anode leak area for hydrogen leak detection using an adaptive alarm limit. Although these methods are easily implementable, hard thresholds typically are prone to high false alarm rates and missed detections due to uncertainties arising from noisy measurements and operating conditions.

4.2. Fuzzy logic-based methods

Fuzzy logic-based methods have been used throughout literature to improve the simple threshold-based methods. These methods use knowledge-based reasoning to construct logical rules to diagnose faults. This concept was applied using the model-based approach to fault diagnosis in cables, transmission lines [63,64] and PV inverters [65]. Neural Networks (NN) have been used to estimate critical parameters of the diesel generator [66], where the fault type, size, and location were determined using fuzzy logic based methods. For data-driven approaches, fuzzy logic based methods have been applied for wind turbines fault detection [67,68] using voltage and current measurements. By virtue of the simplicity of these logical rules, fuzzy logic-based methods are easily implementable with logical gates.

4.3. State estimation-based methods

Several methods try to estimate the system's state by constructing state observers [69] based on real measurements or model generated data via comparing the measurements with their theoretical estimates. The state-estimation based methods are typically useful when all of the state parameters are not observable.

Model-based approaches either construct reduced order models of the system to reduce complexity or design state observers to fill in sensor gaps in the physical system. Arcak et al. [70] utilized the state estimation-based method to estimate the partial pressure of hydrogen in the anode channel of a fuel cell. The estimate was then used to identify membrane degradation faults. Bachir et al. [71] detected and diagnosed rotor and stator faults of induction machines through comparison of the estimated model parameters that represent the magnetic state of the system with their prior information. An interesting method was used by Drews et al. [72] and Stettler et al. [73] for detecting module faults of PV panels by estimating the solar irradiance from satellite images. The estimated values were compared with the model-based simulation data for a healthy condition. They showed that the irradiance parameter estimate can diagnosis module faults of a PV panel without the use of monitoring units that measure output signals. By estimating stack voltage, excess oxygen, and compressor motor speed, compressor motor, hydrogen leaks, and supply manifold faults are diagnosed in fuel cells based on the power measured at the supply manifold [74]. Short/open-circuit faults of PV panels can be identified using NN as well. Syafaruddin et al. [75] used NN models to estimate the terminal module voltages from the overall voltage and current measurements at the output of the panel for parameter estimation.

Data-driven approaches use measurement data from the real system to estimate the system state. Based on data generated from an actual fuel cell, this method was utilized by Fouquet et al. [76] for flooding and drying faults in fuel cells. They modeled the system health state using Randles circuit to fit parameters such as membrane resistance, polarization resistance, and diffusion resistance that capture the different operating characteristics. A data-driven state-estimation approach was also applied to wind turbine faults' diagnosis by using vibration, wind speed, temperature, and power measurements [68]. They developed a state estimator using NN trained to generate the expected outputs during the nominal operating conditions and then compared with actual measurements of the real system.

4.4. Classification-based methods

Several classification algorithms have been employed in literature for fault diagnosis in the electrical energy infrastructure of micro-grids. A classifier is an algorithm that takes data or transformed data (e.g., features) as an input and emits out a decision about the health status of the system. Several classification-based methods are described as follows:

- *Neural Network based classifiers*: Neural Networks (NN) [77] used as classifiers, map data generated from physical models or the real system to a failure mode. In literature, these classifiers typically consist of an input layer, hidden layers, and an output layer of neurons. Each layer consists of multiple neurons that are connected through edges that carry weights. In the training phase, these weights are trained such that the NN model can estimate the failure mode present in the system from the data measured. The output data from the NN classifier will identify if a fault is present in a simple, quick and efficient manner.

This method was used to construct a classifier based on simulation data for detection and localization of cable and transmission line faults [78–83] in power grids. Chao et al. [84] also used NN to diagnose module faults in PV panels based on the maximum voltage, current values at the maximum power point and open circuit voltage.

Similar to model-based approaches, data-driven approaches also use NNs to diagnose faults. The only difference in the design of the NN based models is that they use real data to train the model. This method was used to classify gearbox faults in wind turbines [85,86]. A neural network was trained using experimental data and subsequently used for fault detection through a comparison of the real-data vs the output of the trained neural network.

- *Decision tree-based classifiers*: decision trees [77] create a logical structure that systematically compares two classes at each level allowing multiple binary classifications to improve overall performance. Chouder and Silvestre [87] estimated losses in PV panels during module faults to help diagnose short and long term power loss faults. They then developed a diagnostic decision tree that allows for fault isolation to understand the underlying failure mode based on data generated from a detailed model.

  This method was also used based on data generated from the real system. For example, utilizing voltage, current, and fill factors as features, PV panel module faults can be isolated using decision trees [88].
- *Support Vector Machine (SVM) classifier*: another classification algorithm known as Support Vector Machine (SVM) [77] is also used. SVM classifiers project the data to a high-dimensional space using a kernel function, where the classifier finds the optimal hyper planes that can separate different types of fault classes yielding high classification accuracy. This classifier was applied to cables and transmission lines for line fault diagnosis and localization [89–92] using a model-based approach.
- *Feature extraction-based classifiers*: Sometimes faults occurring in distributed generation systems are difficult to capture using raw sensors data, especially when under the influence of non-linearities, noise, and other uncertainties. Thus, data pre-processing steps are necessary to identify some useful features from the data that can enhance the separability between different faults. For example, features can be extracted using different statistical measures derived from the system parameters. By identifying the correct features, data from different faults are arranged into separable clusters in the feature space, thus enabling the classifier trained on this feature space to diagnose faults.

  Based on data generated from detailed models, this method was employed by Esobet et al. [48] by calculating relative fault sensitivity features. These features were calculated using the residuals computed between the real and theoretical values of the oxygen excess ratio, compressor current, compressor speed, and stack voltage to form clusters in the feature space that isolate the compressor motor faults, flooding, and failed temperature controllers in a fuel cell. Feature extraction-based methods enable a transformed view of the data that often lead to better classification of faults.

  Feature extraction methods are also used in data-driven approaches to separate data measured from a real system. Kurz et al. [93] employed a simple method for fuel cell diagnostics using the real and imaginary parts of the impedance spectra, high frequency resistance, and flooding indication value, respectively, to reliably predict flooding and drying of the cell. This was then used to provide protective control strategies to ensure system reliability. A method known as the *Principal Component Analysis* (PCA) [77] allows for feature extraction as principal components from sensor data. PCA was used on the current and voltage outputs of a diesel generator to detect rotor and stator faults [55]. Once the features were extracted from the data, the k-Nearest Neighbor (k-NN) [77] classifier was implemented. This classifier was trained by forming clusters of each class in the feature space. Then, when testing data arrives, it is transformed to the feature space where the k-NN classifier counts k nearest points, and chooses the class of the test point based on the majority vote of the neighborhood points.

  Another method for feature extraction was based on constructing a Probabilistic Finite State Automaton (PFSA) from sensor data using methods of symbolic dynamics [94]. This method was used to diagnose the amount of carbon monoxide present in hydrogen streams for fuel cells. Hatch [95] calculated the acceleration envelope of wind turbines by passing the vibration measurements through either a high-pass/band-pass filter to identify frequencies that can detect bearing faults. They identified that these frequencies determine fault signatures that clearly separate the faulty bearing specimen from the healthy specimen.

4.5. Domain transformation-based methods

Other methods investigate the frequency domain characteristics of data to capture fault signatures.

- *Fourier transform based methods*: the Fourier transforms allow for the spectral analysis of the steady state signals and can be utilized to classify faults. This was employed using a data-driven approach based on vibration, wind speed, power, voltage and current measurements to diagnosis gearbox and electrical winding faults in wind turbines [38]. Vibration analysis was also conducted for diesel generators using frequency analysis [96]. A variation of this method was used by Jeffries et al. [97] called the bispectral analysis. This utilizes the Fast Fourier Transform (FFT) to create a two-dimension Fourier transformation. Utilizing the magnitude of this transformation, called the bicoherence, peaks of the data were amplified to increase the reliability of fault signatures. This method was also used as a feature extraction method paired with the SVM classifier to diagnose faults in diesel engines [98].
- *Wavelet transform based methods*: another method is to use Wavelet Transforms, which are useful to map the time series signals into a 2-dimensional domain that depicts the information at different scales and time shifts. This was applied to cables and transmission line faults using a model-based approach by transforming the voltage and current measurements to capture fault signatures [99–102]. These domain transformation-based methods are similar to feature extraction-based methods in the sense that they project the data to a space where the separation between fault classes is enhanced.

In addition to fault classification problems, technical literature has also addressed the fault localization problem. For example, for cables and transmission lines [103–105], signal impulses are sent throughout the cables for measuring the spike locations that indicate the locations of the fault.

This section presented a review of the state-of-the-art methods of fault diagnosis for the energy infrastructure of micro-grids to identify the failure modes as presented in Section 3. This review also provides a benchmark for developing control methodologies for fault mitigation that can be built upon the tools of early diagnostics.

5. Conclusions and recommended future work

Fault diagnosis of the energy infrastructure of micro-grids with high penetration of renewable energy sources is essential for reliability of power distribution by facilitating condition based maintenance and minimization of cascading failures. This paper provided an overview of the fault universe of the various components of a micro-grid and the state-of-the-art diagnosis methods in terms of model-based and data-driven approaches.

The methods presented here inform the readers of the different solution methods available in literature to address the issues of fault diagnosis. However, depending on the monitoring technology, communication infrastructure, availability of physical models, and measured data, some solution approaches may perform better than the others due to the difference in the problem formulation. For example, if the real data measured from the physical system is available while a detailed and accurate model of the system is lacking, then the data-driven approaches would work better. In contrast, if a detailed and reliable model of the system exists that can effectively model the healthy and faulty scenarios, then a model-based approach could be utilized. Another example is that of a user who is in the system design phase and would like to incorporate fault diagnosis into the micro-grid but does not yet have any monitoring data available. In this case, the designer can utilize this review to investigate the diagnostics approaches to propose monitoring technology design and built-in-test placement. Thus, this review will enable the readers to identify the best diagnosis strategy for their system as well as consider alternative system designs to improve the monitoring capability of the micro-grid.

This review will also aid in developing future micro-grids to include control methodologies for fault mitigation through early diagnostics. Some recommended directions for future research are presented below:

- Study of system-wide effects of single or multiple component faults on the micro-grid
- System-level diagnostics of coupled component failures, cascading failures, and ambiguity fault groups,
- Identification of sensor gaps for fault diagnosis,
- Decentralized control for fault tolerance and mitigation based on early diagnostics, and
- Rapid optimization for intelligent reconfiguration for robust and resilient power generation.

Through the integration of fault detection, diagnosis, and control strategies, future micro-grids will possess the ability to sustain power in a distributed manner while increasing the reliability and resiliency of power distribution network.

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