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Fault detection and diagnosis methods for green hydrogen production: A review

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Abstract

One of the green hydrogen projects is ZEHTC¹, in which solar panels, PEM electrolyzer, and diaphragm compressor are used to generate power, produce hydrogen and store hydrogen at high pressure, respectively. Faults in any components of photovoltaic (PV) systems, PEM electrolyzers, and diaphragm compressors can seriously affect the efficiency, energy yield as well as security, and reliability of the entire system, if not detected and corrected quickly. In this paper, the types and causes of PV systems, PEM electrolyzer, and diaphragm compressors failures are presented, then different methods proposed in the literature for fault detection and diagnosis (FDD) of systems are reviewed and discussed. Special attention is paid to methods that can accurately detect, localize and classify possible faults occurring in a PV arrays. The advantages and limits of FDD methods in terms of feasibility, complexity, cost-effectiveness and generalization capability for large-scale integration are highlighted. Based on the reviewed papers, challenges and recommendations for future research direction are also provided. In this work different model-based approaches are investigated as well as their validation and applications. An overview of different methodologies available in the literature is proposed, which is oriented to help in developing suitable diagnostic tool for PEM electrolyzer monitoring and fault detection and isolation (FDI). Model-based methods provide fault detection and identification, are easy to implement, and could be conducted during system operation.

Keywords

Fault Detection Methods, Green Hydrogen, PEM Electrolyzer, Diaphragm Compressor, PV Panels, ZEHTC

Introduction

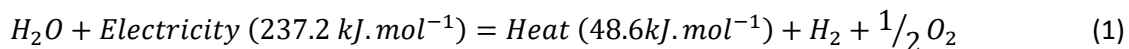
Hydrogen is an essential chemical, already today. However, hydrogen is quickly becoming even more important, as chemical companies, refiners, and new players around the world are looking to build attractive business cases for low-carbon fuels and chemicals. To achieve this, a crucial point is the ability to produce green hydrogen from the electrolysis of water with no carbon emissions. Green hydrogen is produced by electrolysis. This process uses electrical power to split water and produce hydrogen. In the case of green hydrogen, the electricity comes from renewable sources such as wind turbines, solar panels, or hydropower. The electrolysis process emits no carbon or harmful substances.

There has been an increased attention to the photovoltaic (PV) energy systems during the last decade owing to the many advantages that these systems have such as: it is a worldwide available energy source, it is pollution free, it has noiseless operation, it is modular and easy to install, it is a reliable method of energy conversion, and it is able to be installed and/or integrated in the buildings. As a result, the number

¹ Zero Emission Hydrogen Turbine Center

and size of PV systems (PVS) have increased rapidly all over the world. The global photovoltaic market is expected to grow from USD 76.6 billion in 2020 to USD 113.1 billion by 2025, at a Compound Annual Growth Rate (CAGR) of 8.1%. Supportive government policies and initiatives are the primary factors driving the market growth. Moreover, increasing demand for PV systems for residential applications will drive the demand for these products in the near future [1]. Photovoltaic systems are subject to different variety of failures that can involve all PVS components (modules, cabling, protections, converters, and inverters), mainly due to external operating conditions. Faults in PVS are caused by: shading effects, module soiling, inverter failure, and mismatch due to variation in manufacturing or aging of PV modules (PVM). Faults in PVS may cause a huge amount of energy loss as well as risk of fires. Some recommendations for preventing the fire hazards in PVS are reported in [2, 3]. Guidelines for the mitigation of electrical faults that may result in a fire are also given in [4, 5]. To ensure reliable and safe operation of PV installations, monitoring and fault diagnosis systems should accompany these installations to timely detect and solve problems. Addressing these issues, numerous monitoring and fault diagnosis methods have been studied in literature, which vary in rapidity, complexity and sensors requirements, and the capability for the identification of a large number of faults [6, 7]. The main task of fault detection, in PVS, consists of comparing the difference between the measured and calculated parameters with reference values, in order to verify the occurrence of any fault, while the fault diagnosis method aims to identify the type of faults and localize the faults based on a priori knowledge or search techniques [8, 9, 10].

Among many hydrogen production methods, eco-friendly and high purity of hydrogen (99.999%) can be obtained from electrolysis of water to produce pure hydrogen and oxygen it is called as water electrolysis. The basic reaction is described in Eq. (1) [11].



However, the world hydrogen production by electrolysis (mainly brine electrolysis) accounts to only approximately 4% of the total world production [10]. This is mainly due to the fact that the energy required to extract hydrogen from water is about four times larger than the energy required to extract hydrogen from methane. Over the last years, PEM water electrolysis has received a lot of attention. The technology now offers high efficiencies at high current densities and low operating temperatures (<100°C). PEM water electrolysis (sometimes also called solid polymer electrolyte (SPE) water electrolysis) was first developed by General Electric in the 1960s for space applications. It rapidly demonstrated significant advantages over alkaline water electrolysis. Such advantages include (I) the use of non-corrosive electrolytes, (II) significantly higher hydrogen production capacity, (III) higher hydrogen purity, and (IV) higher efficiency at much higher current densities [11, 12]. Proton conducting polymer electrolyte membranes are the main component of the PEM electrolyzer. They act as cell electrolytes and cell separators to prevent the direct mixing of hydrogen and oxygen. Typical membrane degradation in a fuel cell results from mechanical, thermal, and chemical mechanisms occurring over time or under harsh operating conditions. Mechanical damage includes membrane cracks, tears, punctures, and pinholes as a result of uneven stress or other mechanical factors, and is often the main cause of early failures, especially for very thin membranes. According to numerous experimental results, membrane degradation is strongly dependent on operating conditions such as temperature, humidity, freeze-thaw cycling, transient operation, and start-up/ shut-down [13]. The performance of MEA in water electrolysis can be affected by impurities in a number of ways. Metallic cations from feed water can contaminate MEA by exchanging

with protons in the Nafion polymer electrolyte of the MEA [14]. After producing hydrogen, it is time to store it at high pressure, and this is done by the compressor.

Safety has been a major concern in hydrogen applications. Diaphragm compressor is one of the only allowed to trace leaks or not allowed to leak gas compression equipment. As the diaphragm type compressor has a small clearance volume, no pollution, and good cooling effect and other characteristics, and in a small volume, high-pressure oil-free lubrication conditions on the process gas without pollution, particularly suitable for inflammable, explosive, toxic, and hazardous medium, therefore it is widely used in small flow pressurized systems [15]. Due to numerous vulnerable parts in the diaphragm compressor, such as the metal diaphragm, sealed O-ring, self-acting valve, and piston rings, faults frequently occur in the diaphragm compressors and cause unscheduled shutdowns [16]. To date, few studies have been conducted on condition monitoring and fault diagnosis of the diaphragm compressors. Nevertheless, some technologies of monitoring pressure, vibration, and acoustic emission have been used to fault diagnose compressors. For compressors, the primary tool for the determination of diaphragm compressor performance is the pressure-volume (P-V) diagram [17]. Typical approaches to recording the dynamic pressure signal in the cylinder are the installation of the pressure sensor within the cylinder or alternatively within compressor valves through the pressure extraction hole. Researches have indicated that vibration and acoustic emission signals are applied to the non-destructive fault identification and detection of the machines, such as diesel engines, turbines, and compressors [18]. Compressors contain many components moving in both rotary and reciprocating motions that cause the vibration signal to be noise. Finally, the advantages and limits of the various methods are presented and discussed.

Types of faults

PV Panels

Any type of fault that occurs in PV panels leads automatically to unexpected safety hazards, reduced efficiency, power availability, systems reliability and safety. Different kind of defects in PV modules are reported and discussed. These include discoloration, cracking, snail tracks, antireflection coating damage, bubbles, soiling, bus-bar oxidation and corrosion, and split encapsulation over cells and interconnections, back sheet adhesion loss, etc. Generally, faults in PVM can be classified into two main categories: permanent and temporally [19]. Permanent faults are, for example: delamination, bubbles, yellowing of cells, scratches and burnt cells. So, this category of faults can be eliminated simply by replacing the faulty modules. While, temporal faults are basically due to partial shading effects, dust accumulation (soiling), dirt on PVM, and snow that can be removed by operators without replacing the faulty PVM. In addition, the cause of the fault could be external or internal, and both may lead to a decrease in the output power, efficiency and reliability of the PVS. The main faults that may occur in a PVS are summarized in the following. Fig. 1, shows main components used in the construction of a solar panel.

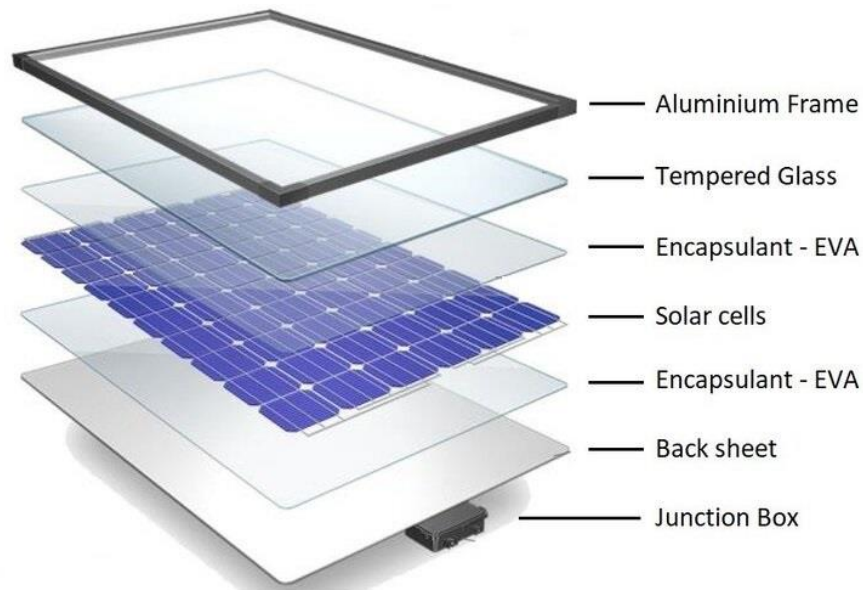


Figure 1. main components used in the construction of a solar panel [20].

a. Encapsulation Failures

The main function of an encapsulated material is to protect the components of a PV module from foreign impurities and moisture along with the fortification from mechanical damage. Encapsulate also acts as an electrical insulator between cells, interconnects and other module components to prevent leakage current and bind all the components together. However, encapsulation failures occur in both early and long-term degradation.

Discoloration and Delamination

One of the major reasons of encapsulation failure is Discoloration and Delamination (D&D). The D&D affects the intensity of solar energy converted to electricity. Thus, it reduces the PV output power as short circuit current is dropped by the decrease in reflectance and transmittance caused by D&D [21]. Module degradation is directly related to the delamination, which has led to deterioration in cell interconnection [22, 23].

Moisture Ingress

Moisture ingress is another cause for encapsulation failure and a reason for the increase in series resistance [22]. Modules can be constructed with impermeable front, and back-sheets where moisture can diffuse in from the sides, or they may be constructed with a permeable sheet where they will equilibrate more quickly with the environment. Even with impermeable front, and back-sheets, water can permeate and condense [24]. Therefore, the incoming irradiation is partially blocked by the moisture and the cells are partially shaded. This results in some cells that are not producing the expected current, and may become reversed biased with respect to the other cells in the string if the shading becomes severe [21, 25].

Module Broken Glass

Shattering of the top glass is due to thermal stress, handling, wind, or hail [26, 27]. Also, installation, transportation, maintenance, and operation process contribute to crack propagation. Module broken glass may keep the module functioning correctly. However, the risk of an electric shock, heavy-metal emissions, fire outbreak, and moisture infiltration increases in addition to the reduction of PV performance by several percent of total capacity [28]. Glass notches and scratches of module glasses could

be the origin of this failure, but the impact is not comparable to a breakage in the module glass itself; that is associated with the aforementioned risks and should be considered as common cause failure that requires an immediate repair [28].

b. Back sheet adhesion losses

The solar panel back sheet is significant material of the solar panel. It is the last layer at the bottom of the PV module and is made up of a combination of polymers. It protects solar panels against environmental damage (ultra-violet radiation, humidity and vapor penetration, dryness, wind, dust and sand) and ensures that panels remain electrically insulated. The form and the composition of back sheet materials can determine this fail [29].

c. Hot spots

Hot spot heating occurs in a PV module when its operating current exceeds the reduced short-circuit current of a shadowed or faulty cell or group of cells. When such a condition occurs, the affected cell or group of cells is forced into reverse bias and dissipates power, which can cause local overheating. Hot spots degrade PV panel and reduce performances of PV plant. Shading, bypass diode failure and mismatch between electrical characteristics; all these factors contribute in the development of hotspots [30, 31, 32].

d. Bubbles

This type of degradation is similar to delamination but in this case, the loss of Ethylene Vinyl Acetate (EVA) adhesion only affects a small area and is combined with the surface swelling whose adhesion was degraded. The bubbles are generally due to chemical reactions that emit gases trapped in the PVM. When this happens on the back side of module, congestion appears either in the encapsulating polymer or on the back side of the module thus forming the bubbles. They make it more difficult for cells heat dissipation, increasing their overheating and reduce then their lifetime [33]. In Fig. 2, a PV module with a large number of bubbles on the back side is shown. They usually appear in the center of the cell and may be due to poor adhesion of the cell caused by the high temperature [34]. Bubbles located on the module front side can produce a reduction of the radiation reaching the module; they cause a decoupling of the light and increase reflection [34].

e. Diodes fault

Bypass diodes are used in PV modules to prevent the application of high reverse voltage across the cells in the event of shading. These are the requirements: I) It should have low forward voltage and fast switching characteristics. So, Schottky diodes, which are semiconductor-metal junction-based, are used for solar modules. II) Bypass diodes should have a low leakage current. III) The maximum repetitive reverse voltage of the bypass diode is directly linked with the number of cells bridged by the bypass diode. Bypass diodes can fail in two modes: short-circuit mode and open-circuit mode [35]. To avoid this type of fault, both the bypass diodes and blocking diodes should be chosen carefully and tested adequately [36].

f. Junction box fault

The junction box is the container fixed on the backside of the module which protects the connection of cell strings of the modules to the external terminals. Generally, the junction box contains the bypass diodes to protect the cells in a string in case of hot spot or shadowing. Observed failures in the field are: a) Poor fixing of the junction box to the back sheet. Some adhesive systems are good for short-term pull but poor for long term adhesion. b) Opened or badly closed j-boxes due to poor manufacturing process. c) Moisture ingress which cause corrosion of the connections and the string interconnects in the junction box d) Bad wiring causing internal arcing in the j-box. This failure is particularly dangerous because the arcing can initiate fire [37].

g. Cells cracking

Cell cracks appear in the PV panels during their transportation from the factory to the place of installation. Also, some climate proceedings such as snow loads, strong winds and hailstorms might create some major cracks on the PV modules surface [38]. These cracks may lead to disconnection of cell parts and, therefore, to a loss in the total power generated by the PV modules [39].

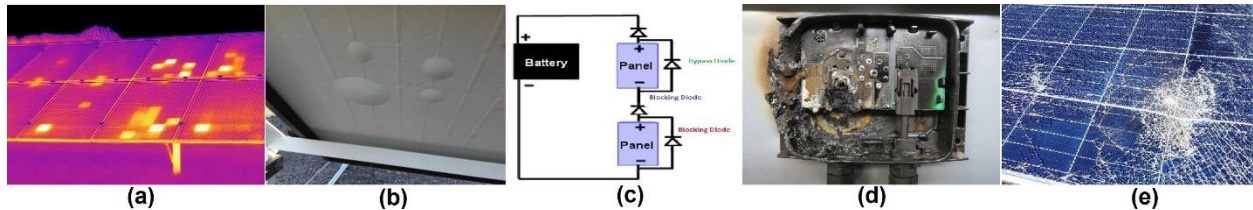


Figure 2. Module defects: a) hot spot, b) bubbles, c) burnt bypass diodes, d) junction box, e) cells cracking.

h. Soiling losses

Soiling losses refer to loss in power resulting from snow, dirt, dust and other particles that cover the surface of the PV module. Dust is a thin layer that covers the surface of the solar array, and the typical dust particles are less than 10 μm in diameter but this depends on the location and its environment. Dust is generated from many sources such as pollution by wind, pedestrian volcanic eruptions, and vehicular movements among many others. The accumulated dust over time aggravates the soiling effect. In fact, the amount of accumulated dust on the surface of the PV module affects the overall energy delivered from the PV module on a daily, monthly, seasonal and annual basis [40].

i. Shading losses

Two types of shading exist [41]. The first type is hard shading; which occurs if PV panels are shaded by a solid material, or buildings. The second type is soft shading; it can be caused by smog in the air. The first one results in a voltage decrease. The second one affects the current and not the voltage. Both affect PV module performance [40]. The performance and power loss are related to shaded surfaces. In fact, shaded cells behave as a resistance to generated current [41]. They heat up and result into hot spot.

j. Light induced power degradation

Light-induced degradation (LID) refers to a loss in the silicon solar cell efficiency that is observed during excess carrier injection by above-bandgap illumination [42] or forward biasing. LID is seen as a decrease in the solar cell short-circuit current and the open-circuit voltage, caused by increased minority-carrier recombination in the bulk of crystalline silicon [43]. Although LID has been studied extensively for the past four decades, the recombination-active defects responsible for degradation remain yet to be identified.

k. Ground fault

A ground fault in PV arrays is an accidental electrical short circuit involving ground and one or more normally designated current-carrying conductors. Ground-faults in PV arrays often draw people's safety concerns because it may generate DC arcs at the fault point on the ground fault path. If the fault is not cleared properly, the DC arcs could sustain and cause a fire hazard [44].

l. Line-line fault

It is an unintentional short circuit connection between two different potential points in PV panel. This failure takes place between two points belonging to the same string or among two adjacent strings. It may be undetected and presents important loss [45].

m. Arc fault

It occurs due to discontinuities and insulation breakdown in current carrying conductors or adjacent ones. Series and parallel arc-faults produce high frequency noise in DC current of PV string, and parallel arc fault results in additional sudden voltage/current drop inside PV array [46]. This type of failure is very dangerous for the plant, and may produce fire [47]. Fig. 3, shows respectively the soiling, shading, line-line, and, arc defects that can appear on PVM.

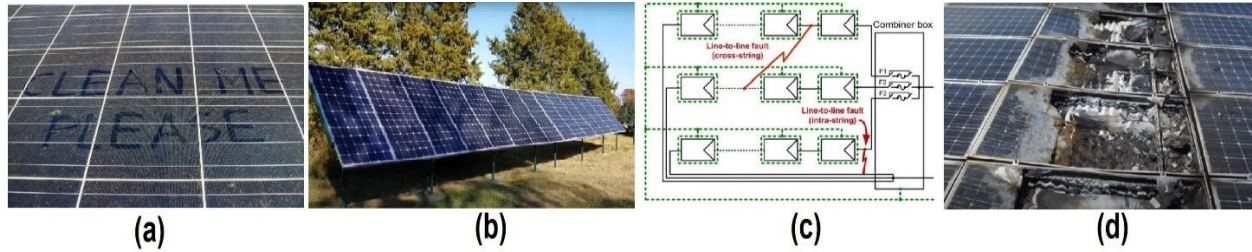


Figure 3. Module defects: a) soiling, b) shading, c) line – line [48], d) arc fault.

Table 1. Summary of different type of faults in PV.

Type of fault	Affected components	Causes	Effects	Impact on performance
Encapsulation	Cells / Module	Fragmentation of cells, Fretting corrosion, Loosen and oxidation, Glass breakage	Damage of solar cells Damage PV Module	Medium
Back sheet adhesion	Module	Manufacturing defects, Aging Scratches, Damage due to mechanical damage	Damage PV Module Damage PV Module's connection	Low
Hot spots	Cells / Module	Soiling, Snow, Dust, Shadow, Aging, degradation of cells, Current mismatch between cells, High resistance or cold solder points	Damage of solar cells Open circuits Reduce efficiency and reliability	High
Bubbles	Module	Manufacturing defects, Encapsulation	Reduce efficiency	Low
Diode faults	Bypass diodes or Blocking diodes	Overheating, Partially shaded cells	Damage diodes Short circuited diode Open circuited or shunted diode	Medium
Junction box	Junction box	Loosen and oxidation, Fretting corrosion	Damage and risk of fire Reduce efficiency and reliability	High
Cells cracking	Cells	Hailstone, Changes in air temperature	Damage of solar cells Reduce efficiency	Low
Soiling	Module	Dust, Soot	Reduce efficiency	Low
Shading	Module	Daylighting obstacles (Cloud)	Reduce efficiency	High
Light induced power degradation	Cells	Aging, Daylighting obstacles, Manufacturing defects	Reduce efficiency	Low
Ground fault	PV Array or PV String	Insulation failure of cables Incidental short circuit between normal conductor and ground Ground faults within PV Modules cable insulation damage during the installation Insulation damage of cables. Accidental short circuit inside the PV combiner box.	Reduce efficiency Risk of fire	High
Line-line fault	PV Array	An unintentional low impedance current path between two points. Insulation failure of cables Incidental short circuit between current carrying conductors	Damage PV Modules and conductors Risk of fire	High
Arc fault	PV String	A short break is created in a conductor. Two conductors of widely differing voltage are placed near one another. Degradation in solder joints, wiring or connections inside the insulation damage due to mechanical damage, aging, or wild life junction box, loosening of screws.	Damage of PV string Risk of fire	High

PEM Hydrogen Electrolyzer

PEM water electrolysis offers an efficient and flexible way to produce “green-hydrogen” from renewable (intermittent) energy sources. Their operation involves however, several scientific fields, which results in strongly correlated parameters. This makes these systems particularly complex and hard to control, and increases the probability of fault occurrence.

a. Membrane deterioration

This type of fault takes place with time in terms of the system’s evolution towards new equilibrium points. In this case the diffusion constants of the system are significantly altered and the pressure gradients between the cathode and anode channels drop. The electrolyzer membrane gradually becomes thinner under pressure and working environment conditions. As a result of membrane thinning, hot spots can form and gas cross-permeation effects can increase. The hydrogen content in the oxygen gaseous production and the oxygen content in the gaseous hydrogen production both tend to increase with time. As a result of Perfluorosulfonic Acid Membranes (PFSA) chemical degradation and membrane thinning, the probability of membrane perforation increases dramatically [49 – 53].

b. Leakage

H₂ gas has a high propensity to leak due to its very small size and its low density (0.09 g/L at NTP of 0°C / 1 atm) which corresponds to a high buoyancy. In PEM electrolyzer, hydrogen is prone to leak from seals present at process connections near the H₂ storage cylinders and associated flow paths. While it is nearly impossible to reach 100% gas containment in a PEM electrolyzer stack, reliable leak detection is essential for minimizing loss [54 - 55].

c. Ohmic voltage drop

Ohmic losses are an electrical over potential introduced to the electrolysis process by the internal resistance of the cell components. This loss then requires an additional voltage to maintain the electrolysis reaction, the prediction of this loss follows Ohm's law and holds a linear relationship to the current density of the operating electrolyzer [56 – 57]. As the thickness of the membrane decreases, the amount of this resistance will decrease, and if it falls below a certain value, it means that the membrane is destroyed [58].

d. Cross-permeation

The most critical problem in a PEM electrolyzer caused by the high-pressure operation is the cross-permeation phenomenon that occurs across the PEM during electrolysis. In this phenomenon, hydrogen and oxygen produced at both sides of the electrode permeate through the PEM and then mix together at the respective counter electrode compartment [59 – 60]. This mixing increases the danger of gas explosions and increases the concentration of impurity gases.

e. Absence of catalyst

This fault happens when the catalyst falls out for some reason reducing the active area of the cell, and thus causing a huge deterioration in the cell’s performance. This type of fault was tackled in by the use of Electrochemical Impedance Spectroscopy (EIS) as previously discussed. Moreover, the same technique discussed in the membrane deterioration section was also used to detect a catalyst problem. The authors noted that if the output power of a cell increases with the decrease of the load resistance then the cell’s catalyst is invalid [61 – 64].

f. Carbon monoxide poisoning

Carbon monoxide poisoning is one of the major health concerns in PEM electrolyzers. Research showed that as the CO content in the supplied fuel increases, the cell's performance degrades. This is because CO poisons the anode reaction by adsorbing to the platinum surface and thus blocking the active sites [65 – 66].

g. Reactant Leakage in the electrolyzer stack

In PEM electrolyzers, there is always an accepted leakage rate that should never be exceeded since hydrogen gas is generally known for its high combustibility, especially when confined in small non-ventilated spaces. Once the leakage rate is increased due to cracks in the graphite plate, seal ruptures or membrane cross-leaks, there would be a critical hydrogen concentration due to the accumulating hydrogen in a small space leading to an inevitable explosion [67].

h. Aging

Durability is one of the major limiting factors of the electrolyzers technology. PEM electrolyzers are known to have a short lifetime after which their performance starts to degrade significantly. In [68], a pattern recognition based approach was used to estimate the electrolyzers operating time and its remaining life duration using dynamic stack information based on electrochemical impedance spectroscopy (EIS). Two feature extraction methods were employed in the process: using an empirical model for feature extraction on polarization curves to extract and keep only relevant descriptors and using a latent regression model to automatically split the imaginary part of the spectra into several segments that are approximated by polynomials. Both approaches were evaluated on real data sets and were able to estimate the electrolyzers lifetime with a mean error of 214 hours over a global operating duration of 1000 hours using the first method, a mean error of 142 hours using the second method and a mean error of 95 hours, when using features extracted using both methods [69].

i. Flooding

Since PEM electrolyzers operate at relatively low temperature values ranging from about 60°C to 80°C, water management is always a key issue. The cell's membrane has to be fully water saturated in order to enhance its ionic conductivity. However, if the membrane becomes flooded with water, this would obstruct the gas transport to the reaction sites thus reducing the active surface area of the catalyst. This would significantly increase the cell's activation and concentration losses which therefore reduces the cell's efficiency [70].

j. Drying

If the membrane dries out, its resistivity increases also causing a reduction in the cell's efficiency. Moreover, if the cell operates for a long time with low water content this would significantly reduce its lifetime [71]. Note from Fig. 4. that flooding and drying result in the same V-I characteristics except for when the cell's voltage reaches below its minimum rated voltage. Most of the researches conducted in the area of PEMFC fault diagnosis focus on flooding and drying of the membrane. The voltages of independent cells in a stack differ from one another. It is generally noted by many researchers that the cells nearest to the fuel inlet have higher voltage than those farthest (nearest to air inlet) due to the uneven gas distribution or water flooding. Moreover, it is generally noted that the temperatures of the center cells are relatively higher than the rest and thus they are at a higher risk of drying but rarely get flooded since flooding usually occurs at the cooler cells [72].

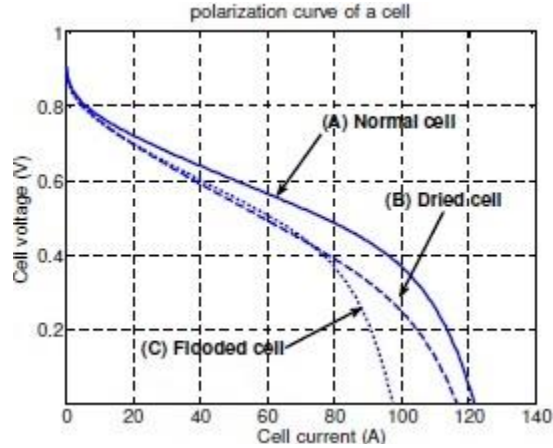


Figure 4. Effect of drying and flooding on the polarization curve.

k. Humidification Failure

As explained previously, the cell's membrane has to be fully water saturated in order to enhance its ionic conductivity. In case the humidifier coupled with the PEMFC failed, the membrane will dry out thus reducing the cell's efficiency. Millet et al. [73] proposed an approach that utilizes the DC/DC convertor that is already coupled with the electrolyzer to perform an online fault diagnosis on a PEM electrolyzer. The DC/DC convertor was controlled by a digital signal processor (DSP) and a capacitor was added in parallel to the electrolyzer stack in order to reduce the current harmonics. Then the PEM electrolyzers online state of health was judged using impedance spectroscopy by injecting a low sinusoidal current signal to the cell at different frequencies. It was noted that with the use of the DSP controller, no pulse width modulation noise was present at the cell's output. The authors then illustrated how the EIS can be used to give an indication on the cell's humidification. The higher the percentage of humidification, the lower is the measured impedance. Moreover, the spectroscopy can also be used to judge the gas flows since the impedance tends to increase with the decrease of gas flows at constant loads [74].

l. Power Electronics Interface Failure

PEM electrolyzers and PEMFCs are usually coupled with DC/DC converters in order to boost the fuel cell's voltage and provide adequate power to the load. However, the large variance between the magnitude of the input and output signals imposes severe mechanical stress on conventional DC/DC converters. Therefore, some researchers started modifying the conventional converters' topology to better suit the electrolyzer application [75].

m. Cooling System Failure

The temperature of the PEMFC is maintained at a desired value using a cooling system in order to ensure high reaction efficiency over all operation. A failure in the deployed cooling system will reduce the cell's efficiency. In [76], a control strategy for a fuel cell cooling system was presented based on a μ -synthesis linear controller which helped maintain performance robustness despite the presence of parameter and input uncertainties.

n. Sensor Network Failure

In case of a faulty sensor or in case of failure of the communication system between the sensors and the controllers then the controllers will fail to control the PEM electrolyzer system. Communication system failure was tackled in [77] using extension neural network (ENN). Moreover, in another approach, a Principal Component Analysis (PCA) model of the fuel cell was developed and then trained in order to detect sensor network failure in PEMFC operated vehicles [78].

Table 2. Summary of different type of faults in PEM electrolyzer.

Type of fault	Affected components	Causes	Effects
Membrane deterioration	Membrane	Aging, Hot spot High pressure	Pressure gradients between the cathode and anode channels drop
Leakage	Fuel distribution channels	Manufacturing defects Aging, High pressure	Risk of fire and explosion
Ohmic voltage drop	Membrane	Membrane thinning	Reduce efficiency and reliability
Cross-permeation	Membrane	High pressure	Damage of membrane and reduce efficiency
Absence of catalyst	Membrane	Aging	Reducing the active area of the cell
Carbon monoxide poisoning	Membrane	Flow rate	Reduce efficiency and reliability
Reactant Leakage in the electrolyzer stack	Fuel distribution channels	Manufacturing defects Aging, High pressure	Risk of fire and explosion
Aging	Stack	Manufacturing defects Aging	Risk of fire and explosion
Flooding	Fuel distribution channels, Membrane	Flow rate, Aging, Manufacturing defects	Reduce efficiency and reliability
Drying	Membrane	Flow rate	Damage of membrane and reduce efficiency
Humidification failure	Membrane	Flow rate, Aging,	Damage of membrane and reduce efficiency
Power Electronics Interface Failure	Stack	Aging, Manufacturing defects	Reduce efficiency and reliability,
Cooling System Failure	Stack	Aging, Manufacturing defects	Risk of fire and explosion, Reduce efficiency and reliability
Sensor Network Failure	Stack	Manufacturing defects, Aging	Reduce efficiency and reliability, Risk of fire and explosion

Diaphragm Compressor

Safety has been a major concern in hydrogen applications. Due to numerous vulnerable parts in the diaphragm compressor, such as the metal diaphragm, sealed O-ring, self-acting valve and piston rings, faults frequently occur in the diaphragm compressors and cause unscheduled shutdowns.

a. Pipeline or valve problems

Pipeline or valve problems mainly include pipeline leakage and the valve do not work in two aspects. Pipeline leak, such as loosening of the joint, valve pressure pipe deflection will cause the exhaust volume reduction. The inlet, exhaust valve of the compressor is a one-way valve; gas can only follow a specific direction through the valve, not by reverse. Usually, the reasons the valve does not work properly are stem locknut off, stem sliding by blocking, the spring is damaged or deformed, the valve port doesn't seal tightly. When the intake valve cannot open properly, the gas entering the compressor decreases, and will eventually lead to the discharge of the compressor reductions; the same when the exhaust valve cannot open properly, gas will reduce exhaust from compressor; when the valve outlet is sealed not strictly, also can cause exhaust to reduce [79 – 80].

b. Oil pressure drop

Oil discharge pressure does not meet the requirements also means the volume of fluid in the hydraulic cylinder is insufficient, the most direct reason is low oil pressure in the oil supply pump. Low oil pressure in the oil supply pump may be caused by the inlet oil filter plugged, gear pump oil pulls down, the inlet, exhaust oil valve doesn't seal strictly or steel ball stroke too large, deterioration of oil or oil spill too much. Among them, low oil pressure in gear pumps may be caused by low oil level in the crankcase, pressure regulating valve limit down, coarse strainer clogging, or gear meshing clearance is too large [81].

c. Diaphragm warpage

The diaphragm itself has a certain elastic force, moves between an upper limit and a lower limit during operation. However, when the cylinder head bolt preload is too large, the diaphragm causing warping deformation, the diaphragm will not be able to reach the upper and lower limit, resulting in a reduction of the compressed gas in the compression cycle, eventually leading to the reduction of compressor discharge [82].

Table 3. Summary of different type of faults in Diaphragm Compressor.

Type of fault	Affected components	Causes	Effects
Pipeline or valve problems	Oil and fluid system	Manufacturing defects Aging	Pressure drop, Loudly noise
Oil pressure drop	Hydraulic cylinder	Oil, Leakage	High temperature
Diaphragm warpage	Diaphragm	Aging Manufacturing defects	Damage of compressor Loudly noise

Fault detection and diagnosis methods

Monitoring systems (MS) are crucial for controlling, supervising and performing fault detection of photovoltaic plants, PEM electrolyzers, and diaphragm compressors, therefore many systems have been recently proposed aiming to perform a real-time monitoring of those instruments.

Fault detection methods for photovoltaic systems are numerous (electrical characterization, visual inspection, ultrasonic inspection, infrared imaging). Some methods use appropriate equipment (thermal camera). These visual inspection or the thermal detection methods, require visual checking with frequent visits on the PV module to monitor changes in its appearance as indicators of failures: browning, mechanical damage or occurrence of hot spots. Electrical diagnostic methods specifically use the electronic signature of faults. They continuously monitor the PV module performance until the appearance of a fault. The deformation of the resulting output provides information on the occurrence, location and nature of default. The first indication of module degradation is provided by decrease in its output power. Resulting symptoms are presented by the I-V curves of electrical characterizations of the PV module. After detection, microscopic analysis can be performed to understand causes of the degradation. These techniques allow analysis of the induced degradation and its progression.

PV Panels

a. Methods based on Radiation

Thermography

When assessing parameters gained through electric measuring, it is necessary to disconnect the cells and especially the modules from the rest of the device and to measure them separately. In the case of PV modules, this method can be quite expensive as well as rather time-consuming with less accessible installations [83]. Thermography is one such method that is frequently used in diagnostics of faults of PV installations. The method works at a principle of detection of thermal irradiation using an appropriate detector. The cells in the module are connected serially. Therefore, when an ideal state is considered where all the cells are identical, the same current flows through them while having the same voltage, they have the same short circuit current. When the short circuit current flows through all the cells, the voltage is zero. In the case of one faulty cell, the current and voltage proportions in the circuit change as given in [84]. Fig. 5, shows different faults by the radiation method.

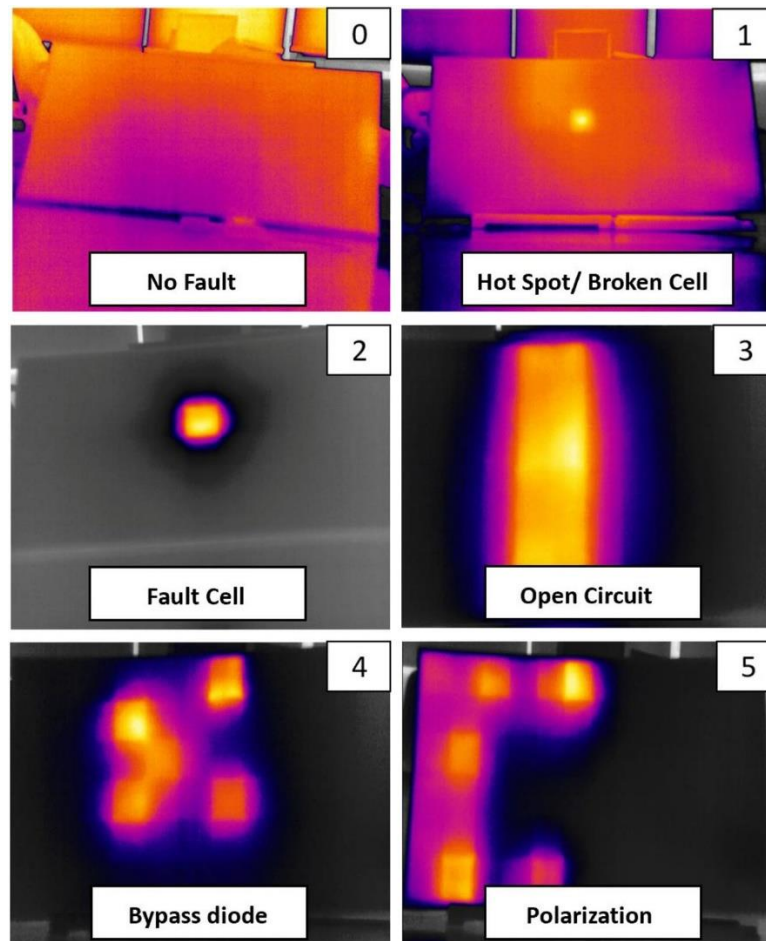


Figure 5. Panel fault thermographs for faults: 0-No Fault, 1-Hot Spot/Broken Cell, 2-Fault Cell, 3-Open circuit with bypass diode, 4-Bypass diode, 5-Polarization [85].

Electroluminescence

Electroluminescence imaging [86] is developing to an established tool for quality assurance in solar cell characterization. It is non-destructive and easy to apply, since only contacting and camera are needed. This method is utilized for cells and modules' defects like cracks, technological defects, and other inhomogeneity's evaluation. Thus, it can also serve as the visual evaluation of the modules. It works at the principle of electroluminescence radiation detection which is emitted by recombined charge carriers during the radiative recombination process [87]. One of the most important properties of a solar cell observable with luminescence imaging is the local series resistance (R_s). It has a significant influence on the fill factor and thus on the efficiency. The origin of high R_s values from I –V characterization are in most cases not homogeneously distributed but may vary laterally. Contact forming problems at the firing process, broken fingers, or bad properties of the screen printing paste cause locally increased R_s values. R_s imaging allows identifying of such causes and to optimizes these steps of production [88].

b. Online (Real Time) Fault Detection

The diagnosis enables detection, isolation, and identification of a fault that reached a critical threshold. Detection of this fault consists of indicating whether a failure appears on the concerned system. The isolation of a failure is meant for locating the failed component and then comes the identification of its nature [89, 90]. Overall, this is to compare in faulty condition threshold with system operation in nominal condition. There are many approaches and the choice of one technique depends on:

- data collected on the system in normal operation conditions
- knowledge of the history of system events
- the expert system knowledge
- a known model of the system

c. Methods based on the Signal-Processing

The main idea of these methods is to apply signal processing advanced techniques to diagnose the PV system faults. One of the methods is time domain reflectometry, and which has been applied at the aim of detecting the faults occurrences, localizing the faults positions, and finally diagnosing the exact faults natures (short circuit fault, open circuit faults, or reverse polarity of the module fault) [91]. Despite the fact that time domain reflectometry can detect, localize, and diagnose faults in PV systems, it suffered from two essential drawbacks and which can be summed up as: the system should be turned off to be capable of applying the TDR method which affects the system productivity, and the need of very sophisticated tools to introduce the input signal and analyze the reflected one hence the cost issue [92].

Reflectometric systems can be regarded as closed-loop radar's: a step-voltage excitation propagates down the electrical line under test, while the voltage is monitored by an oscilloscope. The signal propagates down the transmission line consisting of the PV modules and the series-connecting wires and is partially reflected when a faulty module is reached, producing in the waveform a delayed replica of the input pulse. Measured delay allows us to calculate the distance traveled by the signal and so provides an indication of the fault position [93].

d. Methods based on the power losses analysis

Correct supervision of PV systems operation is important to minimize output power losses and for detecting fault and breakdown of components. A good PV system supervision algorithm must determine malfunctions in the system behavior. The first step is to identify the inherent losses present in the whole

system, in order to establish the boundaries in which the system is under normal operation [94]. At the first stage of energy conversion, the incoming irradiation “Input energy”, will be reduced by shading, reflection due to the angle of incidence and dirt on the surface of the PV modules before this energy reaches the solar cells. The next stage is the photovoltaic energy conversion process where the efficiency is usually defined for the standard test conditions so that it will be always different under real weather conditions. The solar cell temperature is defined as 25 °C where the crystalline silicon solar cell has a negative temperature coefficient. Since the module temperature is usually higher than 25 °C, thus there will be some output power losses due to the conversion efficiency. Maximum power point tracking, mismatch of the PV modules due to the non-uniform distribution of irradiance and temperature, partial shading and additional factors leads also to additional power losses at the DC side [95]. Before the converted energy reaches the utility grid, in grid-connected systems, or the load, in stand-alone systems, new power losses will appear mainly due to the efficiency of the power conditioning units, inverters, regulators, etc. [96].

e. Methods based on the I-V characteristic analysis

The I-V curve represents all of the possible operating points (current and voltage) of a PV module or string of modules at the existing conditions of sunlight (irradiation) and temperature. As Fig. 6, shows, the curve starts at the short-circuit current and ends at the open-circuit voltage. The maximum power point, located at the knee of the I-V curve, is the operating point that delivers the highest output power, the electrical parameters derived from an I-V curve are the open-circuit voltage, the short circuit current, the maximum power point, the fill factor, and the series and shunt resistances. These parameters describe the operation state of the module. Monitoring these values gives a clue about the ambient operating condition regarding irradiation temperature and shadow, and also the inner state of the material, to note the electrical and mechanical mismatches [97, 98]. In a healthy PV array the value of these parameters should restrain their steady-state, any variation in each value refers either to a temporary failure or permanent degradation [99, 100].

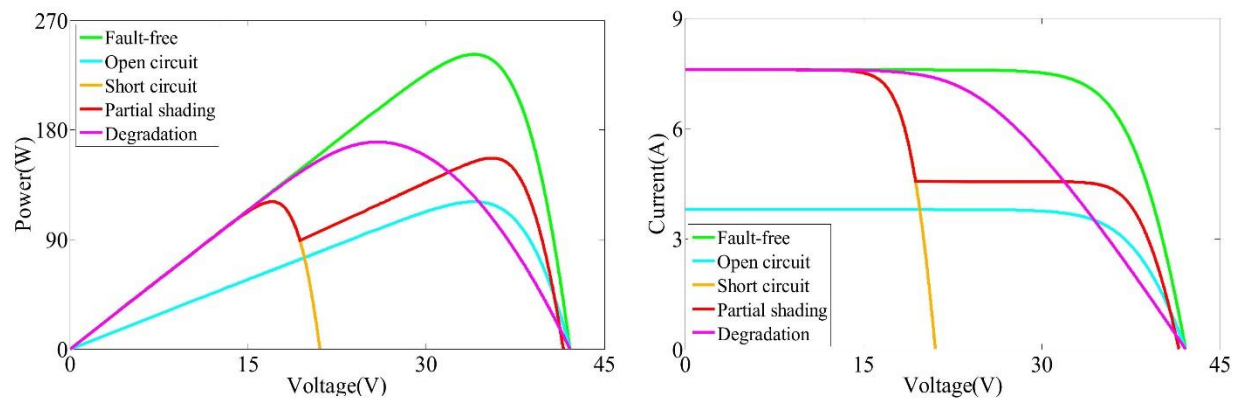


Figure 6. Output characteristics of the PV array under common fault conditions [101].

f. Methods based on voltage and current measurements

Data-acquisition systems are widely used in renewable energy source applications in order to collect data regarding the installed system performance, for evaluation purposes [102]. The mathematical model analysis method compares actually measuring output values with analytically computing output values to detect the fault status of a PV array. But the effectiveness of these mathematical model-based fault detection methods depends heavily on the accuracy of the models [103, 104]. The simple structure and low complexity of the method are the key merits to implementing fault detection for the PV array. As Fig. 7, shows, the single diode model of a solar cell is the most common model used to simulate energy production.

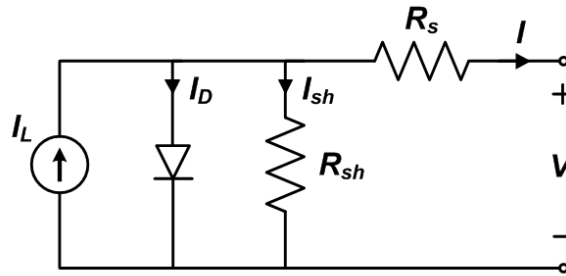


Figure 7. One diode model of solar PV cells and PV modules [105].

The equation that mathematically describes the current and voltage characteristic of the solar cell is given by

$$I_{cell} = I_{ph,cell} - I_{0,cell} \left[\exp \left(\frac{q(V_{cell} + R_{s,cell} I_{cell})}{akT} \right) - 1 \right] - \frac{V_{cell} + R_{s,cell} I_{cell}}{R_{sh,cell}} \quad (2)$$

Where I_{cell} and V_{cell} are the output current and voltage of the solar cell, respectively; $I_{ph,cell}$ is the photocurrent of the solar cell; $I_{0,cell}$ is the reverse saturation current of the diode; a is the diode's ideality factor; T is the cell's temperature; q is the electron charge ($q = 1.602 \times 10^{-19} \text{C}$); k is the Boltzmann constant ($k = 1.381 \times 10^{-23} \text{ J/K}$); $R_{s,cell}$ and $R_{sh,cell}$ are the series and parallel internal resistance, respectively [106].

g. Methods based on artificial intelligence techniques

Artificial intelligence (AI) techniques are becoming useful as alternate approaches to conventional techniques or as components of integrated systems. They have been used to solve complicated practical problems in various areas and are becoming more and more popular nowadays. AI-techniques have the following features: can learn from examples; are fault-tolerant in the sense that they are able to handle noisy and incomplete data; are able to deal with non-linear problems, and once trained can perform prediction and generalization at high speed. AI-based systems are being developed and deployed worldwide in a myriad of applications, mainly because of their symbolic reasoning, flexibility, and explanation capabilities. AI has been used and applied in different sectors, such as engineering, economics, medicine, military, marine, etc. They have also been applied for modeling, identification, optimization, prediction, forecasting, and control of complex systems [107]. The uncertainty associated

with modeling and performance prediction of solar photovoltaic systems could be easily and efficiently solved by artificial intelligence techniques. During the past decade of 2009 to 2019, artificial neural networks, fuzzy logic, genetic algorithm, and their hybrid models are found potential artificial intelligence tools for performance prediction and modeling of solar photovoltaic systems [108, 109].

Table 4. Summary of the different types of methods used for PV system fault detection

Ref	Fault Detection Method Based on	Purpose	Advantages	Limitations
[83-88]	Radiation	Detection & Diagnosis	<ul style="list-style-type: none"> • Can be easily integrated with any method • Low hardware requirements • Physical fault inspection 	<ul style="list-style-type: none"> • Limited fault type identification
[89-90]	Real Time	Monitoring & Detection & Diagnosis	<ul style="list-style-type: none"> • Only require threshold limits from PV model for fault detection • Less component requirement • Easy implementation • Improved detection time 	<ul style="list-style-type: none"> • Accuracy depends on the quality of threshold limits set • Noise in synthetic data may affect fault detection
[91-93]	Signal-Processing	Monitoring & Detection & Diagnosis	<ul style="list-style-type: none"> • Accurate in detection • Minimal sensor requirement • Commercially effective and product oriented 	<ul style="list-style-type: none"> • Presence of noise in sampling signals affects the detection capability • Additional software/hardware platform for feature extraction
[94-96]	Power losses analysis	Simulation & Evaluation & Detection	<ul style="list-style-type: none"> • Accurate in detection • Minimal sensor requirement • Commercially effective and product oriented 	<ul style="list-style-type: none"> • Presence of noise in sampling signals affects the detection capability • Additional software/hardware platform for feature extraction
[97-101]	I-V characteristic analysis	Early identification & Simulation & Detection	<ul style="list-style-type: none"> • Less component requirement • Easy implementation • Minimal sensor requirement 	<ul style="list-style-type: none"> • Noise in synthetic data may affect fault detection • Additional software/hardware platform for feature extraction
[102-106]	Voltage and Current measurements	Simulation & Evaluation & Detection	<ul style="list-style-type: none"> • Only require threshold limits from PV model for fault detection • Less component requirement • Easy implementation • Improved detection time 	<ul style="list-style-type: none"> • Accuracy depends on the quality of threshold limits set • Noise in synthetic data may affect fault detection
[107-109]	Artificial intelligence techniques	Monitoring & Detection & Diagnosis & classification	<ul style="list-style-type: none"> • Ability to diagnose multiple faults • Near Real-Time detection • Performance quantification 	<ul style="list-style-type: none"> • Sensitive to the variations of model parameters • Highly limited applicability to distributed energy resource • High processing requirements • High hardware requirements • Time-Consuming

PEM Hydrogen Electrolyzer

a. Non-Model based methods

A non-model-based method can detect and identify the fault through human knowledge or qualitative reasoning techniques based on a set of input and output data [110]. Non-model based method could be either knowledge-based or signal-based. The objective of this kind of method is to obtain fault information based on heuristic knowledge or signal processing or a combination of both [111, 112].

Statistical methods

Methods based on multivariate statistical analysis offer an alternative for the diagnosis of PEM system. Usually, a huge amount of data from the system can be obtained during different processes, while most of them are highly correlated. In order to extract the most discriminating features from the original data, dimension-reduction methods are highly expected [113]. In practical processes, data collected from different operating conditions are recorded and categorized into different classes. The main idea of the method is to determine a set of discriminant vectors by maximizing the scatter among the classes while minimizing the scatter within each class [114]. According to this characteristic, statistical method can be used to isolate different fault classes and thus help to analyze the fault sources [115].

- **Principle component analysis (PCA)**

Research-based on the multivariate statistical method mainly focuses on fault detection, with that based on the PCA fault detection method being the most popular. The theory of PCA is to build a principal component model under normal working conditions by using the relevance of process variables and to find the fault by testing the divergence of samples from the principal component model. A steady-state working condition refers to a constant running state when all operating parameters remain unchanged during the working process. According to the theory of statistics, process variables are random variables that have near-normal distributions, and the principal component model built under normal steady working conditions, such as a fault detection standard, can describe the statistical features of the system when it is under normal conditions. Therefore, most PCA fault detection methods are studied and used under a steady working state, and a PCA fault detection method under steady working conditions is a basic way to study the other more complicated fault detection methods [116, 117]. In the Soft-Run control strategy [118], the transient condition of the PEM system is broken down into a series of collections of nearly steady working processes. This means it is appropriate to use the PCA fault detection method to test and diagnose the potential faults of a PEM system [119].

- **Fisher discriminant analysis (FDA)**

FDA is another kind of dimensionality reduction technique that shows excellent performance for fault diagnosis. For fault diagnosis, data collected from the plant during specific faults are categorized into classes, where each class contains data representing a particular fault. FDA is a linear dimensionality reduction technique, optimal in terms of maximizing the separation amongst these classes. It determines a set of linear transformation vectors, ordered in terms of maximizing the scatter between the classes while minimizing the scatter within each class [120].

- **Bayesian network (BN)**

Bayesian networks have been extensively applied to fault diagnosis. Bayesian network (BN) is one kind of statistical classifiers. It can be expressed under the form of probabilistic graphical models in which the nodes represent random variables, and the arcs represent conditional independence [121]. Construction

of a BN consists of two parts: finding the network structure and calculating the conditional probabilities from the measured data [122].

Signal processing methods

Many signals obtained from the PEM system processes show oscillations that are due either to harmonic or to stochastic nature, or both. If changes in these signals are related to faults in the process, signal processing approaches can be applied for fault diagnosis [123]. When performing a signal processing-based diagnosis method, there are two things needed to be considered: determining which signals to be applied for monitoring and choosing an efficient signal analysis approach for interpreting [124].

Signal can be decomposed into different modes of oscillations named the intrinsic mode functions that are mono-component signals. Based on the natural variation of the signal, the empirical mode decomposition (EMD) permits the obtaining of a physical interpretation of the signal [125]. In particular, for the electrochemical system, the natural variation of the current could permit us to understand the physical phenomena existing in the membrane electrode assembly and the channel such as the mass transfer, the electrochemical reaction, and the two-phase flow regime at the anode side. In addition to being adapted to the non-stationary signal, the EMD approach is a simple, fast, and non-intrusive method with a low calculation cost. The EMD has no basic mathematical development and is defined by a simple algorithm [126].

- **Fast Fourier Transform (FFT)**

FFT is an important measurement method in the science of audio and acoustics measurement. It converts a signal into individual spectral components and thereby provides frequency information about the signal. The signal is then represented by magnitude and phase components at each frequency. Customarily, the original signal is converted into a power spectrum, which is the magnitude of each frequency component squared [127]. Then significant components can be obtained by analyzing the spectrum. According to the principle of FFT, satisfactory analysis can be acquired only limited to stationary or periodic signals, whose frequencies remain constant. In contrast, when analyzing transitory signals, FFT has poor performance due to its constant time and frequency resolution [128].

Short-time Fourier Transform (STFT) is a modified version of the traditional FF [129]. Having a similar principle to the FFTs, it is easy to understand and apply. STFT was the first time-frequency method, which was applied by Gabor [130] in 1946 to speech communication. The STFT may be considered a method that breaks down the non-stationary signal into many small segments, which can be assumed to be locally stationary, and applies the conventional FFT to these segments. Usually, STFT has good performance for signals that have uniform energy distribution within an analyzing window [131]. However, an apparent drawback of STFT that prevents its wider application is its invariant window size, which will lead to a dilemma between time and frequency resolutions for non-uniform distributed signals. In this case, a good location in both time and frequency for a signal cannot be achieved simultaneously [132].

- **Wavelet transform (WT)**

A major disadvantage of the Fourier Transform is its captures global frequency information, meaning frequencies that persist over an entire signal. This kind of signal decomposition may not serve all applications well. For the analysis of transitory signals, wavelet analysis is another option that mitigates the dilemma between time resolution and frequency resolution. Wavelet theory and its applications are rapidly developing fields in applied mathematics and signal analysis. The wavelet theory was developed

in the late 1980s by Mallat [133], and Daubechies [134]. There are two general types of WT: The Continuous Wavelet Transform (CWT) and the Discrete Wavelet Transform (DWT). The former one is more efficient for the time and frequency resolution of the signal, while DWT has a higher calculation speed [135, 136]. Additionally, DWT has a powerful de-noising capability [137].

Continuous Wavelet Transform

The CWT is defined with respect to a particular function, called a mother wavelet, that satisfies some particular properties. Not every function can qualify to be a mother wavelet. As the kernel function of a signal transform, it is important that the mother wavelet be designed so that the transform can be inverted there must be some related transform that permits one to recover the original signal from its CWT. Even if the application of the CWT does not require such transform inversion, the invertibility of the CWT is necessary to assure that no signal information is lost in the CWT. Signal information may be restructured or rearranged, but it must still be present in the CWT for the original signal to be reconstructed [138]. The continuous wavelet transform (CWT) is defined by Eq. 2 in terms of dilations and translations of a prototype or mother function $\phi(t)$. In time and Fourier transform domains, the wavelet is [139]:

$$\psi_{ab}(t) \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \leftrightarrow \psi_{ab}(\Omega) = \sqrt{a} \psi(a\Omega) e^{-jb\Omega} \quad (3)$$

The CWT maps a function $f(t)$ onto time-scale space by:

$$W_f(a, b) = \int_{-\infty}^{\infty} \psi_{ab}(t) f(t) dt = \langle \psi_{ab}(t), f(t) \rangle > 0 \quad (4)$$

The transform is invertible if and only if the resolution of identity holds [140] and is given by the superposition:

$$f(t) = \frac{1}{C_\psi} \int_{-\infty}^{\infty} \int_0^{\infty} \frac{dad b}{a^2} W_f(a, b) \psi_{ab}(t) \quad (5)$$

Discrete Wavelet Transform

The discrete wavelet transform (DWT) is derived from the discretization of CWT (a, b) and the most common discretization is dyadic, given by [141]

$$DWT(j, k) = 2^j \int_{-\infty}^{\infty} f(t) \psi * dt - 2^j k 2^j \quad (6)$$

where a and b are replaced by 2^j and $2^j k$. An efficient way to implement this scheme using filters was developed in 1989 by Mallat [142]. The original signal, $f(t)$, passes through two complementary filters and emerges as low frequency and high-frequency signals. The decomposition process can be iterated, with successive approximations being decomposed in turn, so that a signal can be broken down into many lower-resolution components.

Artificial intelligence methods

Artificial Intelligence (AI) by definition of [143] is “the art of creating machines that perform functions that require intelligence when performed by people”. AI is also defined based on the eight textbooks between human and rationality centered approaches which are organized into four categories: a) systems that think like humans, b) systems that act like humans, c) systems that think rationally, and d) systems that act rationally [144]. In fact, intelligent approaches and systems have been applied in a wide range of industries and commercial fields. In the field of fault diagnosis, AI has attracted a lot of attention. It is very effective in the recognition of fault patterns or their sources without system structure knowledge. The idea is to find relevant features that describe specific patterns in the feature hyperspace, depending on the state of the system (in normal or faulty operation). There is thus a need to classify the data points and determine which class they belong to [145, 146].

- **Neural Network (NN)**

Artificial neural network is another possibility, which receives significant amount of interest in recent years. Artificial neural network is a network of neurons, which learns very complex functions through a series of nonlinear transformation, and with the advent of deep learning techniques, it has been successfully applied to complex classification tasks such as image recognition and speech recognition. Artificial neural networks have been also adopted to address fault diagnosis problem. However, most of the works utilized shallow neural networks or neural networks with hierarchical structure [147, 148]. The fundamental element is a neuron that has multiple inputs and a single output. Each input is multiplied by a weight, the inputs are summed and this quantity is operated on by the transfer function of the neuron to generate the output. The output is sometimes referred to as an activity level [149].

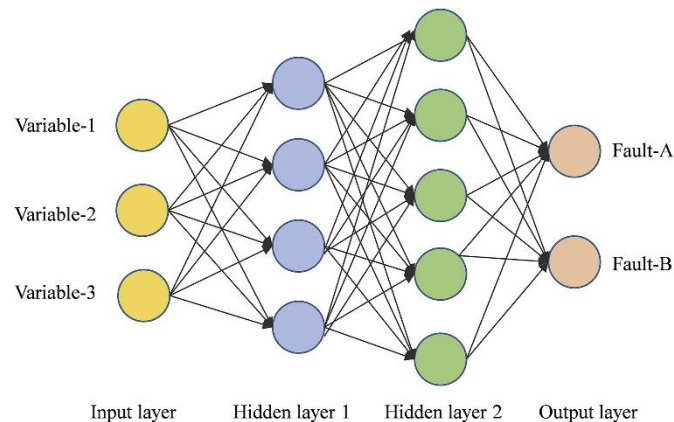


Figure 8. Illustration of the artificial neural network-based fault detection and diagnosis methods.

Artificial neural network classifier is a supervised multi-classifier composed of one input layer, one or more hidden layers, and one output layer. Each layer contains several nodes named artificial neurons which are connected with other nodes in adjacent layers. Each connection has a weight that adjusts as a model training process to minimize the difference between the targets and the outputs [150]. Fig. 8, showed a four-layer artificial neural network classifier for fault detection and diagnosis.

- **Fuzzy Logic (FL)**

A fuzzy logic system is a nonlinear input output mapping of a vector of features into a scalar result, and a knowledge that consists of a fuzzy if-then rule. The starting point of a fuzzy system is to obtain a set of fuzzy if-then rules of domain knowledge of the study. The next step is to incorporate these rules into a

single system [151]. One of the interesting tools for fault diagnosis is fuzzy clustering: the idea behind is the allocation of data points into a number of clusters. Data points with the most similarity will be allocated in the same cluster, while dissimilarities between each cluster will be as large as possible. When used for fault diagnosis, each cluster could represent a certain type of fault in the system. Each data point to be diagnosed can be represented by a vector consisting of a certain number of features that are relevant to the faults relevant fault information [152].

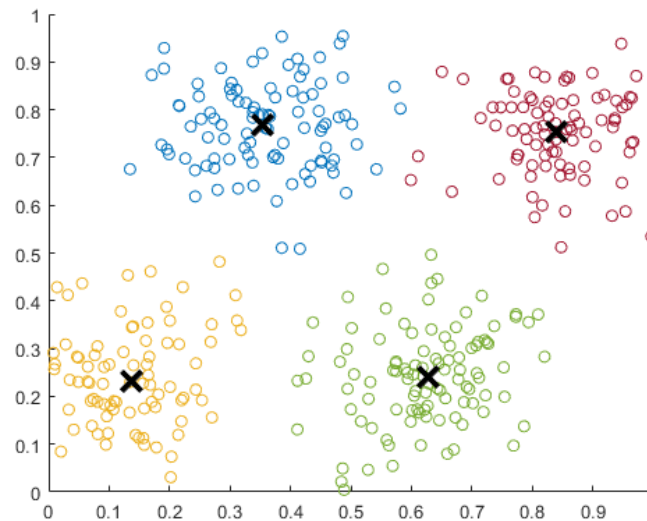


Figure 9. Fuzzy clustering diagram.

Fig. 9 shows a schematic diagram, in which four clusters are obtained on a two-dimensional feature space. Fuzzy clustering has been already widely applied in fields such as image processing, rotating machinery, human activity [153], etc.

- **Neural-fuzzy method**

A new trend in applying AI for fault diagnosis is the combination of FL and NN, of which one most popular form is Adaptive Neuro-Fuzzy Inference System (ANFIS). It integrates artificial neural networks' adaptive capability and fuzzy logic qualitative approach [154]. Neuro-fuzzy system is a fuzzy system that uses a learning algorithm derived from or inspired by neural network theory to determine its parameters (fuzzy sets and fuzzy rules) by processing data samples. The structure of ANFIS is a combination of a fuzzy inference system and a neural network; the summary of this architecture is presented in Fig. 10.

Neuro-Fuzzy system usually is used for approaches that display the following properties: I) A neuro-fuzzy system is based on a fuzzy system which is trained by a learning algorithm derived from neural network theory, II) the system can be viewed as a 3-layer feedforward neural network. The first layer represents input variables, the middle (hidden) layer represents fuzzy rules and the third layer represents output variables, III) it can be always (before, during, and after learning) interpreted as a system of fuzzy rules, and IV) A neuro-fuzzy system should not be seen as a kind of (fuzzy) expert system, and it has nothing to do with fuzzy logic in the narrow sense [155, 156].

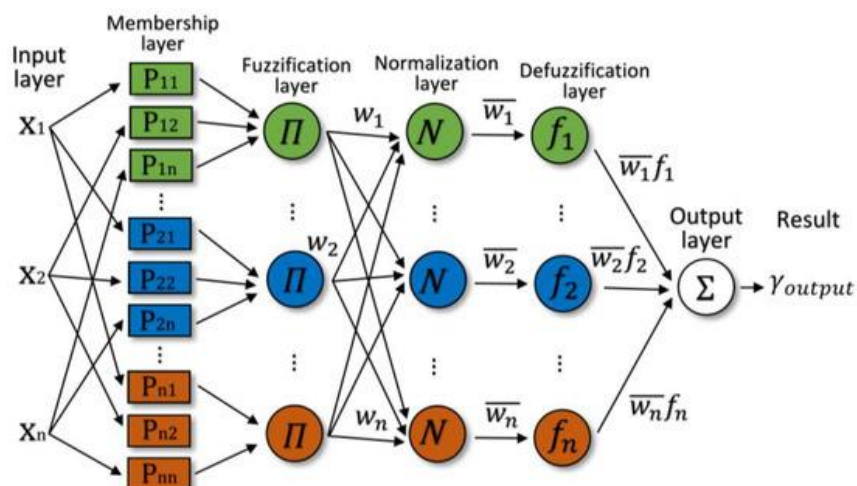


Figure 10. Adaptive Neuro-Fuzzy Inference System (ANFIS) structure for time series evaluation [157].

Electrochemical Impedance Spectroscopy (EIS)

Electroanalytical methods are considered as the most important branch of analytical chemistry, which determines characteristics along with quantity of specific analytic(s) present in an electrochemical cell. The measurement of electrochemical features taking place at the electrode interface reflects the association between the magnitude of the property measured and the concentration of particular chemical species. Compared to other analytical methods, e.g., chromatography or spectroscopy, electroanalytical techniques are much simpler and easier to miniaturize as well as being cheaper, which makes them more appropriate for rapid and accurate detection. Based on the measurable signals, electroanalytical methods are categorized as follows:

- **Potentiometric analysis:**

a reference electrode and an indicator electrode are allocated in a simple electrochemical cell whereas the difference of potential between the two electrodes is recorded to provide significant information about the sample concentration [157]. In the potentiometric technique, at zero current, the potential changes (vs. a reference electrode) are correlated to the changes of a concentration of a target analytic. The EMF of a cell depends on that concentration. Therefore, a direct calculation is easily obtained from the Nernst correlation.

- **Coulometric analysis**

Coulometry is a method to carry out exhaustive electrolysis of an analytic by applying constant potential onto a working electrode surface with respect to a reference electrode [158]. Coulometric titrations are common practices to measure the sample. However, the constant-potential coulometry is not subjected to the effects of interferences, since the potential of the working electrode is controlled at a value at which only a single electrochemical reaction is conducted.

- **Volta metric analysis**

The sample is subjected to a constant/varying potential at the electrode's surface to record the Faradaic current produced. This technique is very important to understand the mechanisms and the kinetics of oxidation–reduction reactions and the electrochemical reactivity of an analytic [158]. The voltammetry

falls into two sub-classes termed as polarography and amperometry. Polarography is a voltammetric technique in which chemical species (ions or molecules) undergo oxidation or reduction at the surface of a polarized dropping mercury electrode (DME) at an applied fixed potential vs. a reference electrode. From the resulting current–voltage (I–V) curve, both the concentration and the nature of the oxidized and/or the reduced substance(s) adsorbed at the dropping mercury electrode surface could be determined [156]. In amperometric methods, redox reactions (oxidation or reduction) of electroactive molecule(s) are measured at a constant potential. Application of voltammetry is widely exploited in biomedical diagnosis and environmental analysis [157].

Cyclic Voltammetry

CV is the basic electrochemical test for materials. In this, the current is recorded by sweeping the potential back and forth (from positive to negative and negative to positive) between the chosen limits. The information obtained from CV can be used to learn about the electrochemical behavior of the material. The graphical analysis of a cyclic voltammogram gives the redox peaks, which are reduction and oxidation peaks of the material, predicting the capacitive behavior of the electrode. Hence, the potential at which the material is oxidized and reduced can be found.

A ramp signal is provided as an input to CV. For the forward scan, a positive ramp (having positive slope) signal is provided, while the voltage is switched after the first half-cycle, followed by a negative ramp, which inverts the nature of the cyclic voltammogram for the second (next) half-cycle. As the system tries to achieve the equilibrium state with the help of redox reactions, it strives to reach the same position where it started. It follows a cyclic pattern, wherein the pattern gives information about the changes that the system has gone through. By properly analyzing the CV curve, one can make many important conclusions regarding the material and its properties (like capacitive nature, etc.) along with the system behavior (reversible, irreversible, or quasireversible). The CV experiment can be carried out with one cycle or multiple potential cycles. The slope of the ramp signal expressed in volts per unit time is termed as the scan rate. The range of this scan rate can be from a few fraction of millivolts per second to several hundreds of volts per second. The scan rate of the system can be varied to get a clear idea of the electrochemistry of the cell. Hence, the scan rate plays a crucial role in the voltammetric behavior of the sample to be tested. Based on the scan rate, one can expect some changes in the oxidation and reduction peak currents along with peak potentials. Also, if the peak current (faradaic current) is increasing with the increasing scan rate, then it represents a good rate capability along with better pseudo capacitive behavior of the electrode material [158]. Higher scan rate results in a higher number of redox reactions due to the presence of the electroactive species at the electrode's (working electrode) surface. For a slower scan rate, however, there is the possibility of missing the peak (either forward or reverse scan peak) owing to the sufficient time available for the products from the reduction or oxidation to participate in a chemical reaction whose products may not be electroactive.

Linear Sweep Voltammetry (LSV)

Linear sweep voltammetry (LSV) and cyclic voltammetry (CV) are the most widely used voltammetric techniques for studying redox reactions of organic and inorganic species because they are unmatched in their ability to provide information on the steps involved in electrochemical processes with only a modest expenditure of time and effort in the acquisition and interpretation of data. These electroanalytical methods require simple and inexpensive instrumentation and provide information not only on electrochemical quantities typical of a redox process, but also on chemical reactions coupled with charge transfer steps. This is because the electrode can be used as a tool for producing reactive species in a small

solution layer surrounding its surface and, at the same time, to monitor chemical reactions involving these products. Moreover, since the relevant responses can be achieved within few milliseconds after the electrode stimulation, they may be used for studying mechanisms involving very fast reactions, thus allowing even short-lived transient intermediates to be detected [158].

LSV and CV techniques were proposed at the beginning of the 1950s and in those years only some theoretical approaches able to rationalize the simplest responses were worked out. The use of these electroanalytical methods has instead received considerable impetus only subsequently (in the 70s-80s), thanks to the increased knowledge of subtler criteria for interpreting the relevant responses and to the greater availability of theoretical tools for processing experimental data.

b. Model based methods

The intuitive idea of the model-based fault diagnosis technique is to replace the hardware redundancy with a process model which is implemented in the software form on a computer. A process model is a quantitative or qualitative description of the process's dynamic and steady behavior, which can be obtained using the well-established process modeling technique. In this way, we are able to reconstruct the process behavior online, which, associated with the concept of hardware redundancy, is called the software redundancy concept. Software redundancies are also called analytical redundancies. Similar to the hardware redundancy schemes, in the framework of the software redundancy concept the process model will run in parallel to the process and be driven by the same process inputs [158]. It is reasonable to expect that the re-constructed process variables delivered by the process model will well follow the corresponding real process variables in the fault-free operating states and show an evident derivation by a fault in the process. In order to receive this information, a comparison of the measured process variables (output signals) with their estimates delivered by the process model will then be made. The difference between the measured process variables and their estimates is called residual. Roughly speaking, a residual signal carries the most important message for a successful fault diagnosis [159]:

if residual = 0 then fault-free, otherwise fault

The procedure of creating the estimates of the process outputs and building the difference between the process outputs and their estimates is called residual generation. Correspondingly, the process model and the comparison unit build the so-called residual generator, as shown in Fig. 10.

Observer-based methods

The basic idea of a model-based FD system for a process is demonstrated by Fig. 11, where a process model is running parallel to the physical process and driven by the same inputs. In fault-free cases, if the process model is perfect and has no disturbances, the process outputs estimated by the model should follow the measured process outputs. In these cases, the so-called residual, which is the difference between the estimated values and the measured values, should be zero [160]. If there is a fault, the residual will be divergent from zero. Hence the residual presents important information about faults of the process. The procedure of creating the estimation and building the residual is called residual generation, and the process model including the comparison function is called a residual generator. In fact, no technical systems can be modeled exactly and there are always different kinds of disturbances. Hence the residual is always influenced by the model uncertainties and disturbances. In order to extract the useful fault information from the residual signals, two strategies have been developed: I) replacing the process model with other advanced residual generators which are robust against model uncertainties

and disturbances. II) evaluating the generated residual signals in order to distinguish the faults from disturbances. The residual post processing and decision logic units are called residual evaluators [161].

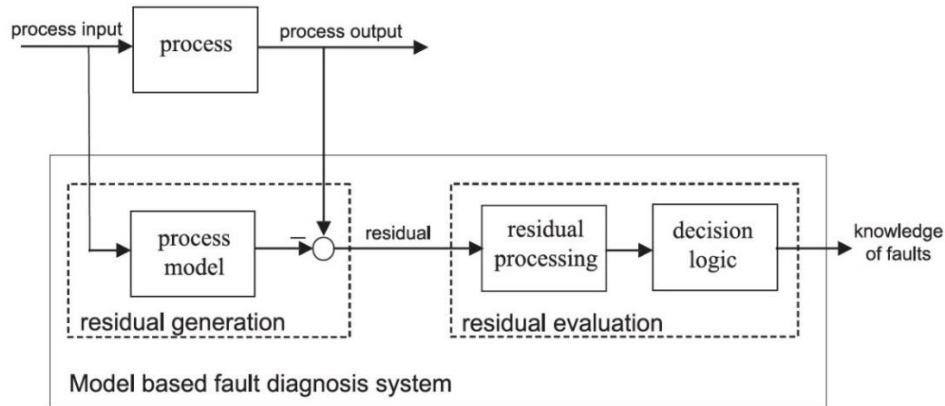


Figure 11. Schematic description of the model-based fault diagnosis scheme.

Parity space methods

Based on the state-space model for the residual region characterization, parity space methods adopt parity relations instead of an observer for a residual generation [162]. In the parity space fault detection and isolation (FDI) framework, residual generation, the dynamics of the residual signals regarding the faults, and unknown inputs are presented in form of algebraic equations. Hence, most of the problem solutions are achieved in the framework of linear algebra. This not only brings with the advantages that, I) the FDI system designer is not required to have rich knowledge of the advanced control theory for the application of the parity space FDI methods, II) the most computations can be completed without complex and involved mathematical algorithms, but also provides the researchers with a valuable platform, at which new FDI ideas can be easily realized and tested. In fact, a great number of FDI methods and ideas have been first presented in the parity space framework and later extended to the observer-based framework. The performance index-based robust design of residual generators is a representative example. Motivated by these facts, we devote throughout this book much attention to the parity space FDI framework. The associated methods will be presented either parallel to or combined with the observer-based FDI methods. Comprehensive comparison studies build also a focus [163 – 165].

Parameter identification methods

In the framework of the parameter identification based methods, fault decision is performed by an on-line parameter estimation, as sketched in Fig. 12. Parameter estimation techniques were amongst the first to be considered for the purpose of performing early fault detection and diagnosis for critical systems. The main advantage of these techniques is their computational simplicity; this makes them suitable for practical implementation within real-time control applications, especially in the context of the recent technological developments regarding parallel computing. Also, the fact that they are designed to provide the estimated model of the impaired plant on which the controller reconfiguration procedure is based

makes these techniques attractive from the point of view of Fault Tolerant Control (FTC) design. On the other hand, the main drawbacks of parameter estimation techniques with respect to the Fault Detection and Diagnosis (FDD) problem are their weak robustness to external disturbances that may affect the system behavior, and the fact that an estimation that is accurate enough is usually time consuming. Recent surveys have shown that the current research priority regarding FDD consists of finding reliable solutions for the real-time implementation of technical diagnosis systems [166, 167]. These systems need to operate under very strict time constraints and offer support to the on-line system reconfiguration and restructuring mechanisms. The existing model-based FDD schemes that use parameter estimation techniques offer good results from the perspective of the suitability for FTC, although a simultaneous state and parameter estimation approach could provide even better global results, see again [166].

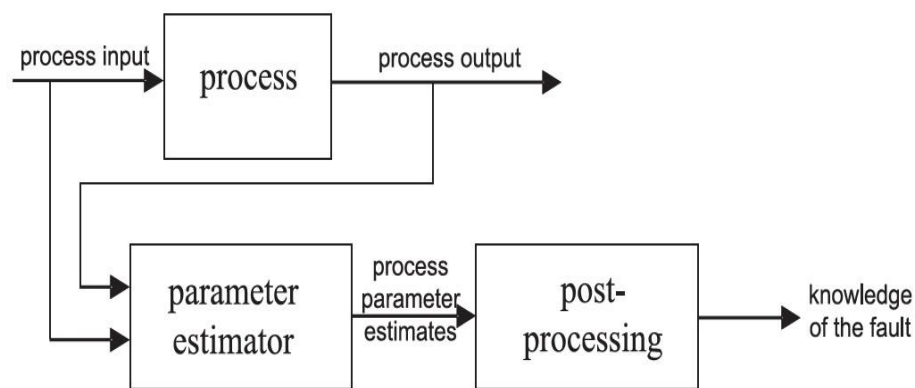


Figure 12. Schematic description of the parameter identification scheme.

Table 5. Summary of the non-model based diagnosis methodologies for PEM electrolyzer stacks and systems.

Ref	Fault Detection Method Based on	Purpose	Advantages	Limitations
[113-122]	Statistical	Detection & Diagnosis	<ul style="list-style-type: none"> • Can be easily integrated with any method • Low hardware requirements • Physical fault inspection 	<ul style="list-style-type: none"> • Limited fault type identification
[123-142]	Signal Processing	Monitoring & Detection & Diagnosis	<ul style="list-style-type: none"> • Accurate in detection • Minimal sensor requirement • Commercially effective and product oriented 	<ul style="list-style-type: none"> • Presence of noise in sampling signals affects the detection capability • Additional software/hardware platform for feature extraction
[143-157]	Artificial Intelligence	Monitoring & Detection & Diagnosis	<ul style="list-style-type: none"> • Only require threshold limits from PEM model for fault detection • Less component requirement • Easy implementation • Improved detection time 	<ul style="list-style-type: none"> • Accuracy depends on the quality of threshold limits set. • Noise in synthetic data may affect fault detection. • The calculation is so huge and the requirement for processor is relatively high.
[157-158]	Electrochemical Impedance Spectroscopy (EIS)	Detection & Diagnosis	<ul style="list-style-type: none"> • Can be easily integrated with any method • Easy implementation • Accurate in detection • Physical fault inspection 	<ul style="list-style-type: none"> • Limited fault type identification
[158]	Cyclic Voltammetry (CV)	Detection & Diagnosis	<ul style="list-style-type: none"> • Can be easily integrated with any method • Easy implementation • Commercially effective and product oriented 	<ul style="list-style-type: none"> • Additional software/hardware platform for feature extraction • Limited fault type identification
[158]	Linear Sweep Voltammetry (LSV)	Detection & Diagnosis	<ul style="list-style-type: none"> • Can be easily integrated with any method • Easy implementation • Commercially effective and product oriented 	<ul style="list-style-type: none"> • Additional software/hardware platform for feature extraction • Limited fault type identification

Table 6. Summary of the model based diagnosis methodologies for PEM electrolyzer stacks and systems.

Ref	Fault Detection Method Based on	Purpose	Advantages	Limitations
[160-161]	Observer	Monitoring & Detection & Diagnosis	<ul style="list-style-type: none"> Allows adopting analytical methods in a discrete time, domain Allows the residual dynamic evolution monitoring Good robustness 	<ul style="list-style-type: none"> Costly method since it requires a lot of things Time-Consuming
[162-165]	Parity Space	Detection & Diagnosis	<ul style="list-style-type: none"> Allows the analytical system equation reconstruction Good robustness 	<ul style="list-style-type: none"> High processing requirements Time-Consuming
[166-167]	Parameter Identification	Early identification & Modeling & Monitoring & Detection & Diagnosis	<ul style="list-style-type: none"> Parameters sensitivity to singularity is considered coupling the Minimum Error method with the Occurrence Number method Use of common commercial software for network analysis Good representation of system dynamics Non-invasive Allows associating singular equivalent circuit components for each physical phenomenon Easy to implement Robust fault detection and isolation 	<ul style="list-style-type: none"> High hardware requirements Costly method since it requires a lot of things

Diaphragm Compressor

a. Based on the acoustic emission (AE) signal

Acoustic emission refers to the generation of transient elastic waves produced by a rapid release of energy from a localized source within the surface of material, as reported by the American Society for Testing and Materials (ASTM) [168]. As Fig. 13, and 14 show, acoustic emission testing works by mounting small sensors onto a component under test. The sensors convert the stress waves into electrical signals, which are relayed to an acquisition PC for processing.

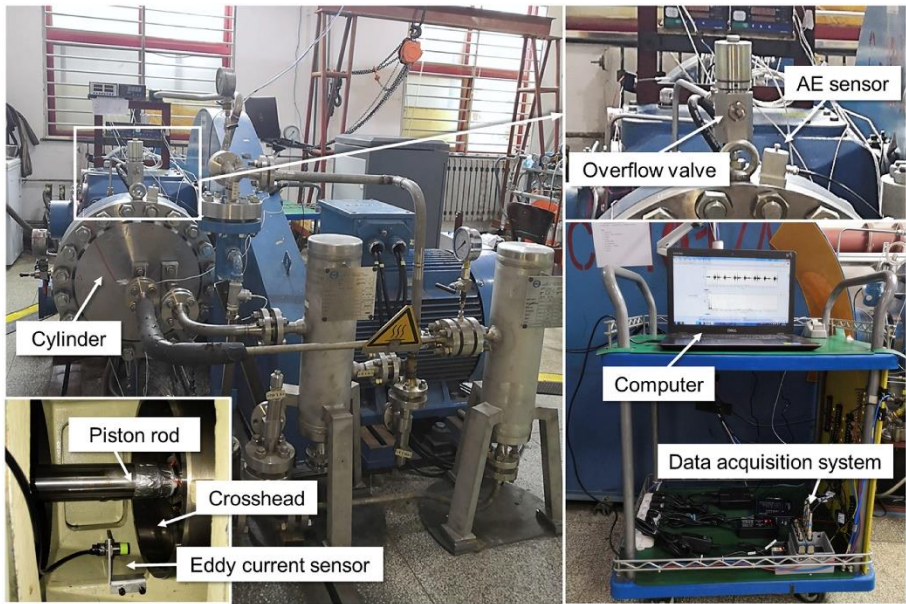


Figure 13. The schematic diagram of the test rig [169].

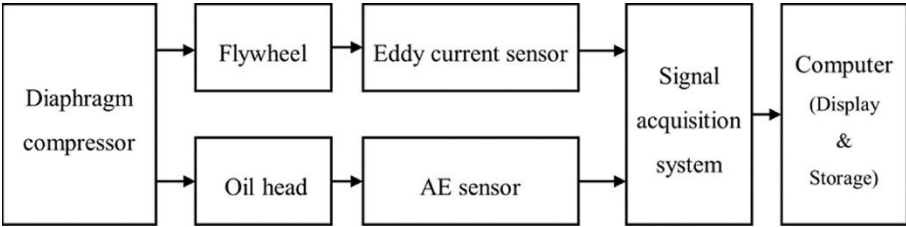


Figure 14. The specific process of test data acquisition for diaphragm compressor [169].

The waves are captured when the component is submitted to an external stimulus, such as high pressures, loads or temperatures. As the damage grows in the component, there is a greater release of energy. The rates in which the acoustic emission is detected, the activity, and the intensity of the acoustic emission, the loudness, are monitored and used for assessing structural integrity and for health monitoring of components. By using multiple sensors, acoustic emission sources (and hence the damage) can be located. Through signal analysis, the presence of different source mechanisms can also be determined [170]. There are two AE testing methods: transient and continuous. The transient method captures AE bursts that exceed a threshold (loudness level) and extract features such as peak amplitude, signal energy and duration of the burst. These features are then

used to assess the condition of the component under test. This method is well suited for testing structures for defects such as cracks [171]. The continuous method captures all AE within a set time period, for example 1/10th of a second. Then, features such as average signal level and root-mean squared values are then extracted. This method is well suited to applications where there is a lot of background AE or AE amplitude is low [172].

b. Based on the vibration data

The vibration signal acquired from a machine in working conditions contains effects of several individual components along with noise. One has to identify and choose the signal which is related to the component under observation. In most cases, the vibration signals are collected from the casing. The presence and type of fault will be detected at the start of development and its progress will be monitored and hence the residual life of the machine guessed [173]. This helps in planning suitable maintenance. Fault diagnosis is conducted typically in the following phases: data acquisition, feature extraction, and fault detection and identification as shown in Fig. 15.

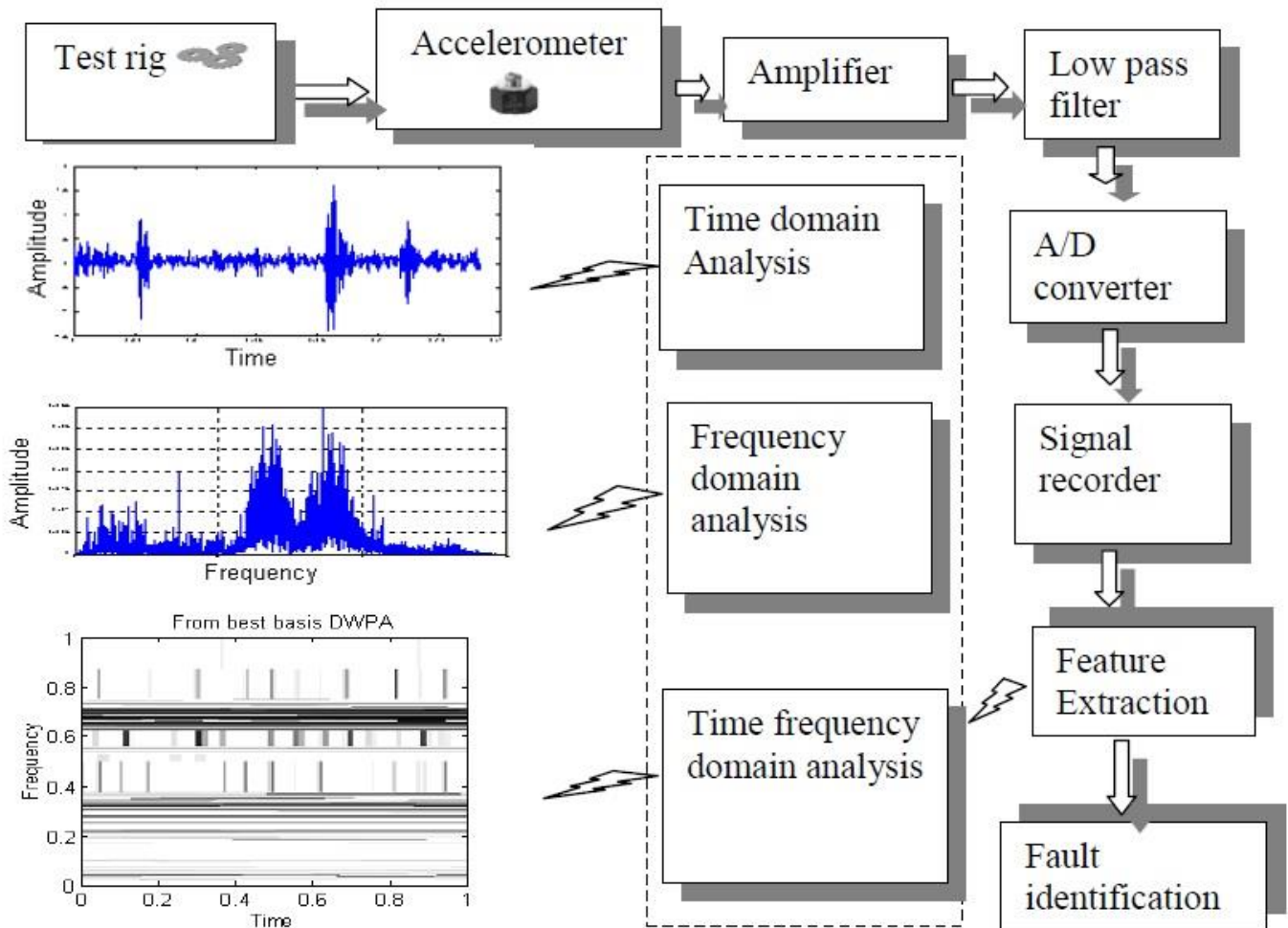


Figure 15. Overview of fault diagnosis based on vibration signals [174].

Signal Processing Techniques

The condition monitoring system involves signal processing techniques. There are different types of faults and processing these signals is crucial. The selection of the appropriate technique depends on the nature of the captured signal. These techniques include [175].

- Time-domain analysis

Time domain analysis involves the analysis of physical signals or time series of data, with respect to time. A time-domain graph is used for visualizing the change in a signal with respect to time [176].

- Frequency domain analysis

Frequency domain analysis involves the analysis of physical signals or time series of data, with respect to frequency. It shows the number of signals lying within the given frequency band over a range of frequencies [177].

- Time-Frequency domain analysis

It comprises the techniques used in both the time and frequency domains simultaneously. This analysis involves the study of two-dimensional signals [178].

c. Based on Thermography

The higher the object temperature is, the faster the particles move. Consequently, more energy radiates outward at higher temperature and vice versa. Based on this principle, infrared cameras convert the infrared radiation energy of objects into electrical signals, and display them in the form of images. Because color images can express a wider color range than grayscale images, and because the color range that a color image can express is wider than the color range that a grayscale image can express, an infrared image is expressed by converting electrical signals into a color image through a specific process such as rainbow encoding or hot-metal encoding. All of these encoding methods have a one-to-one correspondence between temperature and color, so the temperature of the object can be analyzed by analyzing the color of the image [179, 180].

d. Model-based method

To describe the model-based method for condition monitoring and diagnosis, some fluidic basics of compressors are clarified in the following. The most relevant variables to describe the thermodynamic transfer behavior from inlet to discharge are the specific isentropic enthalpy difference Δh_s , the isentropic efficiency η_s and the pressurization $\dot{p}(t)$ of a constant volume V [181].

$$\Delta h_s = \frac{k}{k-1} R_s T_{in} z \left[\left(\frac{p_{out}}{p_{in}} \right)^{\frac{k-1}{k}} - 1 \right] \quad (7)$$

The specific isentropic enthalpy difference describes the difference of the sum of inner energy U and the product of pressure p and volume V between two thermodynamic system states. The behavior of real gases is considered by the specific gas constant R_s and by the compressibility factor z [182, 183]. Besides the pressure ratio between inlet pressure p_{in} and discharge pressure p_{out} as well as the inlet temperature T_{in} , the enthalpy difference Δh_s also depends on the isentropic exponent κ , which describes the ratio between the isobar and isochoric heat capacities [184]. These capacities are assumed to be constant during thermodynamic state changes to simplify the calculation of Δh_s [185]. The thermodynamic transfer behavior is influenced by irreversible processes, friction, so that more energy is consumed than is required to achieve a certain pressure. To take these energy losses into account, the isentropic efficiency has to be considered to describe the relationship between inlet and discharge variables [186]. Besides the pressure ratio between inlet pressure and discharge pressure as well as the isentropic exponent κ , the isentropic efficiency η_s also depends on the inlet and discharge temperatures T_i and T_o .

$$\eta_s = \frac{T_{in} \left[\left(\frac{p_{out}}{p_{in}} \right)^{\frac{k-1}{k}} - 1 \right]}{(T_{out} - T_{in})} \quad (8)$$

As compressors, which convey fluids of variable density, are components with a specific volume V , there is a dynamical behavior of the inlet and discharge process variables in case of a state change. In general, the pressure $p(t)$ within a constant volume V depends on the inflowing and outflowing quantities $\dot{m}_{in}(t)$ and $\dot{m}_{out}(t)$. The pressurization is described by

$$\dot{p}(t) = \frac{kR_s T(t)z}{V} [\dot{m}_{in}(t) - \dot{m}_{out}(t)] \quad (9)$$

The pressure $p(t)$ is calculated by integrating $\dot{p}(t)$ [186]. In this method, parameters such as temperature, pressure, and power are used and for fault detection real power required is compared with calculated power. According to Fig. 16, a technical system underlies deviations, respectively faults in its actuators and sensors as well as faults in the process itself. A fault is an unpermitted deviation of at least one characteristic property of the system from the acceptable, usual, standard condition [187].

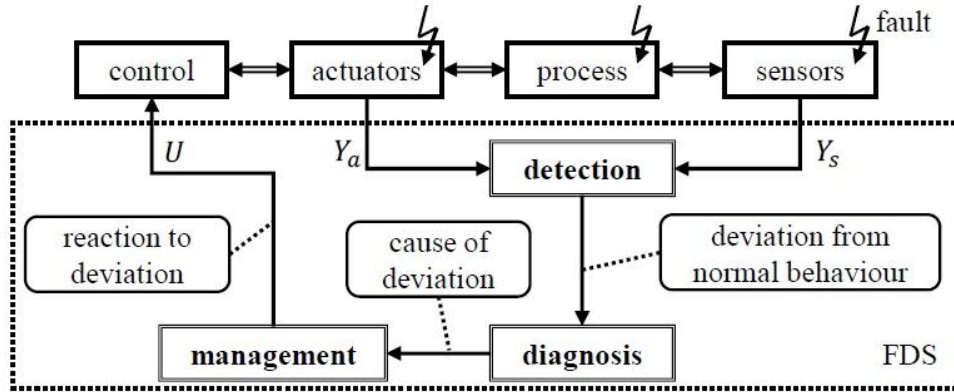


Figure 16. Model - Based fault diagnosis

Table 7. Summary of the diagnosis methodologies for Diaphragm Compressor.

Ref	Fault Detection Method Based on	Purpose	Advantages	Limitations
[168-172]	Acoustic Emission (AE) Signal	Detection & Diagnosis	<ul style="list-style-type: none"> • Ability to detect a range of damage mechanisms including, but not limited to, fiber breakages, friction, impacts, cracking, delamination and corrosion in their early stages, before they become significant issues. • Can be conducted during operation, during qualification (proof) testing or development testing. • Can locate damage sources and can be differentiate these based on acoustic signatures. • Global monitoring of a structure. • Assesses the structure or machine under real operational conditions. • A non-invasive method. • Operational in hazardous environments, including high temperatures, high pressures and corrosive and nuclear environments. • Can be conducted remotely. • Can detect damages in defects that are difficult to access with conventional non-destructive testing techniques. 	<ul style="list-style-type: none"> • Limited to assessing structural integrity or machine health by locating issues, further inspection is usually required to fully diagnose issues. • Cannot detect defects that may be present, but that do not move or grow. • Can be slower than other non-destructive testing techniques.
[173-178]	Vibration Data	Monitoring & Detection & Diagnosis	<ul style="list-style-type: none"> • Accurate in detection • Minimal sensor requirement • Commercially effective and product oriented 	<ul style="list-style-type: none"> • Presence of noise in sampling signals affects the detection capability • Additional software/hardware platform for feature extraction
[179-180]	Thermography	Detection & Diagnosis	<ul style="list-style-type: none"> • Can be easily integrated with any method • Low hardware requirements • Physical fault inspection 	<ul style="list-style-type: none"> • Limited fault type identification
[181-187]	Model-based method	Early identification & Modeling & Monitoring & Detection & Diagnosis	<ul style="list-style-type: none"> • Allows adopting analytical methods in a discrete time, domain • Allows the analytical system equation Reconstruction • Good robustness • Easy to implement 	<ul style="list-style-type: none"> • Costly method since it requires a lot of things. • High hardware requirements • Time-Consuming

Conclusion

Detecting and identifying faults and failures in time can considerably improve efficiency and reliability in different systems. In this study, the most significant recent information available on the performance, degradation and reliability of the PV modules, PEM electrolyzers, and diaphragm compressors has been reviewed. The main conclusions are as follows:

- Most of these methods use recorded on-site measurement electrical. Consequently, depending on the needed sensors, the investment cost can sensitively vary from one fault detection method to another.
- Artificial neural network can be implemented for multiple failure detection. Some of them can also identify the failure types. From a maintenance cost minimization point of view, the best ones are those which identify and localize failures. This is because fault localization is the most difficult and time-consuming process.
- Statistical methods do not require knowledge of previous data. However, they cannot identify the PV system failure type and some of these methods require offline supervision.
- The performances of the methods based on electrical parameters and electrical signal comparisons are sensitive to connection degradation. However, they require an external signal function generator which increases considerably the installation cost and size.
- Model-based methods provide fault detection and identification, are easy to implement, and could be conducted during system operation. However, they require knowledge of previous data and need electrical and meteorological (In PV panels) sensors.

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