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Review

A Survey on Anomalies and Faults That May Impact the Reliability of Renewable-Based Power Systems

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Abstract: The decarbonization of the electricity grid is one of the actions that can help reduce fossil fuel emissions, and thus their impact on global warming in the future. This decarbonization will be achieved mainly through the integration and widespread diffusion of renewable power sources. This is also going to be supported by the shift from the paradigm of production–transmission–distribution, where electricity production oversees large-size power plants, to renewable-based distributed/diffused production, where electricity is generated very close or even by the same (group of) user(s) (or prosumers in the latter case). The number of mid-/small-size installations based on renewable energy technologies will therefore increase substantially, and the related renewable generation will be dominant against that from large-size power plants. Unfortunately, this will very likely reduce the reliability of the grid, unless appropriate countermeasures are taken/implemented, hopefully at the same time that the paradigm shift is being achieved. To this aim, it is important to identify the anomalies and main fault causes that might possibly affect some of the central renewable (wind, PV, hydrogen) and ancillary technologies that will be used to establish future renewable-based power systems. Accordingly, this paper presents a literature survey, also extending the focus to related datasets that can be used for deeper investigation. It is highlighted that the gaps mainly refer to a lack of a common taxonomy that prevents the establishment of structured knowledge in the scope of renewable-based power systems, a lack of contributions to anomalies/faults specific to wind turbines, and a lack of datasets related to electrolyzers, fuel cells, DC/x conversion, and monitoring and communication systems. Further, in the case of monitoring and communication systems, the scientific literature is both very dated, therefore not considering possible new aspects that would be currently worthy of investigation, and not oriented toward the particular domain addressed, thus considering peculiar aspects that are left out.

Keywords: survey; anomaly; fault; power system; renewable energy; renewable integration; dataset

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1. Introduction

The reduction in fossil fuel usage in the future electricity grid is an important measure to alleviate global warming and strive to maintain temperature increases within acceptable thresholds in the future. This process is destined to happen through the advancement of pertinent renewable technologies and their widespread adoption, facilitated by initiatives such as new installations, the overhaul or decommissioning of antiquated fossil fuel-based power plants, and the establishment of a new grid architecture centered around renewable, distributed generation. This evolution may also usher in novel roles, such as those of prosumers, contributing to the diversification of the energy landscape.

It is widely acknowledged that the optimal functioning of renewable-based generation systems necessitates one or more renewable sources (e.g., Photo Voltaic (PV) panels, Wind

Turbines (WTs)) integrated with storage solutions, efficient power conversion units, and complemented by digital technologies (including circuitry and software) for control and seamless interaction with relevant entities. In this scenario, the effectiveness of the deployed solutions in supporting or impeding the decarbonization of the electricity grid depends on their technological maturity.

Crucially, ensuring the expected quality of service from these systems is imperative, as any compromise in this regard could lead to significant systemic failures with far-reaching consequences. This risk becomes more pronounced in the context of small- to mid-size installations, where larger penetration, cost constraints and supply chain heterogeneity may introduce challenges not as prevalent in larger counterparts. As such, meticulous attention to the robustness and reliability of these renewable energy solutions is paramount for achieving a sustainable and decarbonized electricity grid.

While the existing scientific literature compiles a substantial number of publications focusing on specific components or aspects relevant to the topic, there is a notable lack of articles addressing the entire technological mix and beyond (i.e., namely, the conversion and monitoring and communication systems).

For instance, Ref. [1] addresses renewable-based energy systems and presents a review of Machine Learning (ML) techniques for health monitoring. Thus, for instance, the relevant time-scales considered by the reviewed algorithms are larger than those considered by the contribution we propose. Further, the scope addressed is quite different from that of this paper because it reviews ML techniques aiming at health monitoring, while we propose a survey on anomalies and faults in renewable-based power systems not focusing on specific algorithms. In [2], energy systems are still addressed, and the survey is not focused on renewable-based systems. Rather, the authors address Artificial Intelligence (AI) techniques for prognostic maintenance, which is somehow related to anomalies and faults, but this is not our main target. Power systems are addressed by the review in [3]; however, only the electric part is relevant to our main target, while the article we propose reviews anomalies and faults that also affect, e.g., the communication systems in renewable-based power systems. In this regard, Ref. [3] does not specifically consider anomalies and faults, or even renewable energy and general ML applications in power systems. Renewable-based power systems are also addressed in [4]; however, the scope is restricted to those primarily focused on the inverter and targeting cybersecurity instead of anomalies and faults in general. A survey on fault diagnosis in micro-grids can be found in [5], but it does not generally address power systems, renewable energy, or anomalies and faults; also, it is not recent, since it dates back to 2016. The same authors proposed a similar contribution in 2014 [6], addressing faults and fault diagnosis. However, this case also moves away from the focus we propose since only the electrical part is addressed therein. In [7], a systematic review of faults that may arise in smart grids is presented. But the focus is not on renewable-based power systems. Ref. [8] does not focus on a unique system and addresses PV and WT renewable generation. However, for instance, it does not include hydrogen-related technologies as this paper does, or even electrolyzers and Fuel Cells (FCs). This is a major point, since hydrogen is identified as one of the main technologies for storing renewable generation and that will strongly support its diffusion in future power systems. Furthermore, Ref. [8] restricted its review to the monitoring of fault conditions and not on the possible anomalies and faults that may instead happen. In [9], the review targets fault detection methodologies and datasets in district heating substations, and in [10], the review addresses fault location and detection techniques in power distribution systems with distributed generation. In both cases, the target system is more specific, and the scope is not the same as what is proposed in this paper, with renewable generation not being considered at all.

In summary, the analyzed literature is either too specific, by restricting the investigation to particular instances of power systems (e.g., PV systems, district heating substations), with peculiar implemented software (e.g., AI-based) and hardware (e.g., inverter) technologies, and aims (e.g., fault location), or does not sufficiently compile the main renewable-based technologies in one self-consistent article with the focus on the possible anomalies and faults that may affect them. In particular, a substantial gap regards hydrogen technologies, monitoring and conversion systems, where reviews that consider them even within similar frameworks to those identified by this paper are basically missing.

The paper is organized according to the standard format of this journal, and the rest is organized as follows. Section 2 reports some clarifications regarding the terms "anomaly" and "fault" as used in the specific context addressed and more broadly in the scientific/technical community, and the survey outcomes. In particular, Section 2.2 addresses PV systems, Section 2.3 addresses WTs, Section 2.4 addresses electrolyzers, Section 2.5 addresses FCs, Section 2.6 addresses Battery Systems (BSs), Section 2.7 addresses DC/x conversion systems, Section 2.8 addresses monitoring systems, and Section 2.9 addresses communication systems. Section 3 concludes the paper.

2. Materials and Methods

This paper aims to explore the state of the art concerning anomalies and faults of components involved in a renewable-based electrical grid. Specifically, attention was paid to the failure causes and mechanisms of individual components of an advanced power system, while deferring the analysis of events originating from mutual interactions or with other systems/entities (e.g., the energy market) to a future paper.

In order to identify relevant sources, the survey was carried out in two steps:

- In the first phase, anomalies and faults of the components were categorized through a search activity on digital collections such as Scopus, ScienceDirect, Web of Science, and IEEE Xplore, using concatenated keywords related to the component typology (such as "PV" or "Photovoltaic" or "Wind" or "Wind turbine" or "Electrolyzer" or "Electrolysis" or "Fuel Cell" or "FC" or "Battery" or "Battery system" or "BESS" or "Conversion" or "Power conversion" or "Converter" or "AC/DC" or "DC/DC" or "Monitoring systems" or "Communication" or "Communication systems") and the investigated issue (such as "Failure" or "Anomalies" or "Rupture" or "Degradation" or "Performance decay" or "Reliability" or "Stress test"). The analysis of the identified papers and their related bibliographies was used to extend the investigation to other relevant papers.
- In the second phase, empirical datasets or mathematical models for the identified issues of each technology were searched. Through a detailed analysis of the papers highlighted in the previous phase, useful mathematical models or the existence of dedicated datasets were identified. Datasets were also found using platforms such as Google Dataset Search, IEEE DataPort, Kaggle, and Mendeley Data by using as combined keywords the technology and the investigated issue.

2.1. Caveats

Before presenting the outcomes of the survey, some clarifications are needed regarding the terms "anomaly" and "fault". In the scientific/technical literature, their meaning is debated and there is no unique understanding of them. This is well reflected in how the subject is addressed by, e.g., IEEE and NASA, two prominent institutions in the technical field. In the first case, IEEE Std 1044-2009 [11] reports that «*[...] The word 'anomaly' may be used to refer to any abnormality, irregularity, inconsistency, or variance from expectations. It may be used to refer to a condition or an event, to an appearance or a behavior, to a form or a function. The 1993 version of IEEE Std 1044 characterized the term 'anomaly' as a synonym for error, fault, failure, incident, flaw, problem, gripe, glitch, defect, or bug, essentially deemphasizing any distinction among those words. Such usage may be common practice in everyday conversation where the inherent ambiguity is mitigated by the richness of direct person-to-person communication, but it is not conducive to effective communication by other (especially asynchronous) methods [...]*».

On the contrary, in the second case, NASA SP-2016-6105 [12] reports that an anomaly is «*[...] The unexpected performance of intended function*». while a fault is «*[...] A physical or logical cause, which explains a failure [...]* » and relies on how the question is addressed in [13].

The existence of heterogeneous positions regarding the meaning attributed to the terms “anomaly” and “fault” is an element of ambiguity that, e.g., affects the definition of possible taxonomies aiming at the establishment of pertaining structured knowledge.

However, by considering that the surveyed literature makes no difference about the two terms and uses both interchangeably [14]; in what follows, the same convention is kept without any further discussion. Thus, in a broad sense, this identifies a possible gap in the literature that could be filled by a specific contribution on the topic from interested researchers.

2.2. Anomalies and Faults in PV Systems

The survey focused on articles related to PV systems (as shown in Figure 1), realized by arranging with different configurations strings of several PV modules. The output DC power is fed to a DC/DC converter, and the voltage and current are continuously monitored and adjusted within the Maximum Power Point Tracking (MPPT). In the case of grid-connected systems, the DC/DC converter output is fed to a DC/AC inverter (actually, in this case, the DC/DC-DC/AC conversion chain is realized in one power converter unit) and then low-pass-filtered to adequately meet the utility grid standards on power quality (roughly, central frequency of typically 50 Hz or 60 Hz). Finally, before the injection into the grid, the voltage is elevated by a step-up transformer. In some cases, PV systems are also paired with electricity storage, whilst this is neglected since it is separately addressed in the following sections.

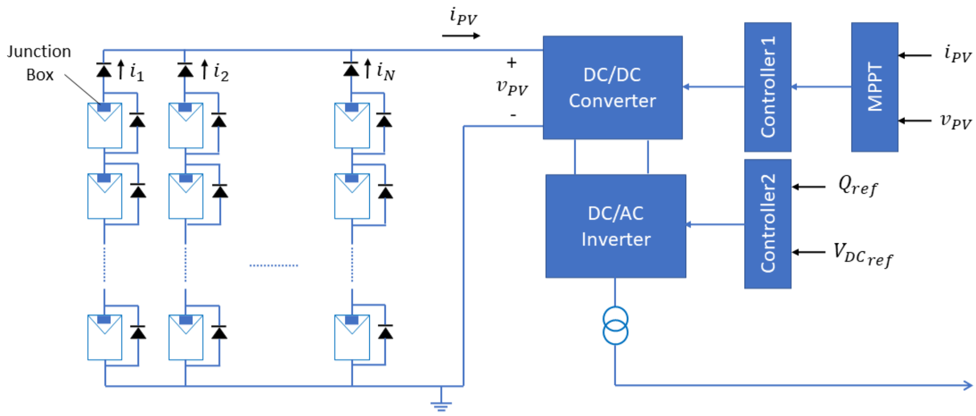

Figure 1. Sketch of a PV system (adapted from [15]).

Research Highlights

The analyzed literature encompasses a diverse array of instances, wherein anomalies/-faults can be attributed to varied and heterogeneous origins. Broadly, an absence of uniform taxonomy emerges among different authors, potentially stemming from the intricate interplay of contributing factors, more realistically manifesting in a domino effect. The authors of [16] group PV anomalies and faults into three categories: internal, external, and electrical.

The internal faults are localized inside the PV module (e.g., under the protective glass, on the strings, on PV cells, etc.). The main internal faults are short circuits, bridgings, faults to bypass diodes and open circuits [17–19]. Their main causes are due to manufacturer defects, subpar fabrication quality, packaging inadequacies, and improper wiring, and have a dramatic impact on PV system. In particular, short circuits entail the failure to supply power to the DC load or the power conditioning unit; bridgings result in no output power; bypass diode faults prevent mitigating hotspot events; and open circuit faults prevent supplying power to the DC load or the power conditioning unit, leading to a partial blackout or to a non-homogeneity in the power production [16].

The external anomalies and faults are located outside the PV module and usually are due to environmental conditions, natural disasters, wrong packaging, installation, etc. Since PV systems are located outdoors, they frequently are subject to environmental stress as high temperatures, rain, and snow. They do not provide nominal power levels because they do not operate under Standard Test Conditions (STCs). Since variations in solar irradiation directly impact the power generation of PV systems [20], with the consequent uncertainties that must be carefully considered [21], certain areas of PV arrays could yield higher power output compared to others (mismatch) due to non-uniform shading from physical obstructions like trees, buildings, overhead power lines, etc. [22,23]. Additionally, environmental factors such as dust accumulation and bird and leaf droppings could lead to partial shading conditions [24,25]. Furthermore, natural events like lightning and storms [26] can have dramatic consequences on the PV modules. Some of the mentioned faults are reversible due to temporary conditions (e.g., partial shading, dust accumulation, etc.). Permanent mismatch faults, instead, are irreversible and can be caused by poor soldering, module degradation, glass breakage, and structural defects due to improper manufacturing processes or environmental conditions like heavy snow loads or frequent temperature fluctuations [27,28]. Since the external anomalies and faults are very diverse, the severity of the related damages varies as well, ranging from nonhomogeneous power production to a complete blackout [16].

The electrical faults are related to perturbations of electrical quantities such as voltage, current, power, etc. The main electrical faults are the ground, line-to-line, and arc faults [29,30]. These faults can have direct consequences on human operator safety (electrocution), severely damaging the equipment (fire) [16]. Finally, other faults can affect other parts of the PV system as MPPT [31], inverter [32].

The results of the survey are presented in Table 1, where the first column specifies the target component, of the system at hand, subject to anomaly/fault, the second column reports a description of the anomaly/fault considered, the third column specifies causal factors, and the fourth column compiles bibliographic references. All similar tables, i.e., related to the literature findings about the other systems addressed by this paper, are organized with the same column names.

Table 1. Main contributions on anomalies/faults in PV systems (adapted from [15]).

Target Component	Description	Cause	References
PV Module	Partial shading	Clouds, trees, building, etc.	[22,23]
	Dust Accumulation	Environmental pollution	[24,25]
	Leaves fall, bird droppings	Environmental pollution	[25]
	Hot Spot	Mechanical and optical degradation of encapsulation	[33]
	Glass breakage	Bad installation	[27]
	Welding	Leaching of silver or copper, solder joint fatigue, bad welding	[28]
	Frame issues	Snowing	[27]
	Microcracks	Multiple (transportation, incorrect installation, vibrations, excessive loads, environmental stress, improper cleaning, etc.)	[34]
	Busbar failure	Incorrect packaging, installation, hail, and/or stone throwing	[35]
	Module degradation	Multiple	[36]
	Discoloration	Multiple	[37]
	Delamination	Multiple	[38]
	Cell breakage	Multiple (production, transport, installation, vibrations, environmental stress, improper cleaning, and maintenance, etc.)	[27,39]

Table 1. *Cont.*

Target Component	Description	Cause	References
Connection System	Short circuit	Bad wiring, bad production process	[17,19]
	Open circuit	Multiple (bad/obsolete wiring, hot spots, cell breakage, bad connections in the junction box, etc.)	[17–19]
	Bypass diode failure	Short-/open-circuit	[17,18]
	Bridging faults	Improper connection between PV modules	[19]
	Ground fault	Insulation deterioration, corrosion, wire cutting, or poor/incorrect connection	[29,30]
	Line-to-line fault	Short circuits by unintentional connections (wearing, bad connection, etc.) between current-carrying conductors with ground/neutral conductors and/or other PV system's parts (e.g., the PV module's frame)	[29,30]
	Arc fault	Gap between conductors by corrosion of connectors, cell damage, solder disconnection, insulation breakage	[29]
Junction Box	Junction box fault	Human errors (insufficient fastening of the junction to the back panel, poor wiring, inadequate assembly, moisture penetration into connectors)	[40]
MPPT	MPPT control system failure	MPPT charge controller or sensors failure	[31]
Inverter	Inverter failure	IGBT, capacitors, inductors, etc. failure	[32]
PV System	Lightning strike fault	Lightning strikes	[26]
PV array	PV array fault	Bad connections	[29,30]
Network grid connection	Line fault	Line interruptions, equipment failures, maintenance services, network configuration, accidents, human error, etc.	[41]

The literature also offers several datasets, summarized in Table 2, obtained from experimental measurements of real plants or simulated through mathematical models, and, in some cases, the anomalies are also simulated. The first column reports the dataset name as specified in the referred online resource; the second column allows to specify, e.g., whether the provided data are from real plants/systems, simulations, lab-scale installations or others; the third column describes the dataset; the fourth column reports the bibliographic reference; and the fifth column reports possible other references of papers that the authors of the dataset ask to cite. Also, in this case, all other tables related to the dataset of the other systems addressed by this paper are organized with the same column names.

Table 2. Anomaly/fault datasets for PV systems.

Dataset Name	Source	Description	References	Related Papers
Fault Detection Dataset in Photovoltaic Farms	Simulations	Simulated 25 kW PV system used for generating data during normal operations, string fault, string-to-ground fault and string-to-string fault	[42]	[43]
PVEL-AD dataset	Real plant	36,543 electroluminescence images of PV panels with no/various defects and backgrounds	[44]	[45]
GPVS-Faults	Lab-scale real plant	Array, inverter, feedback sensor, MPPT controller and grid anomalies/faults	[46]	[47]

Table 2. *Cont.*

Dataset Name	Source	Description	References	Related Papers
PV System Thermography Dataset	Real plant	120 thermal images obtained from a drone	[48]	[49,50]
Mismatching and partial shading dataset	Simulations and real plant	10,000 simulated IV curves (5000 in normal operations and 5000 under mismatch faults), and 2000 real IV curves (1000 in normal operations and 1000 during faults)	[51]	[52]
Partial Shading and Fault Simulation Dataset	Simulations	Simulations of 10 PV panels under variations in temperature and partial shading conditions	[53]	
PV Fault Dataset	Real plant	System with 2 strings of 8 C6SU-330P PV modules under degradation, short circuit, open circuit and shading anomalies/faults	[54]	[55]
Elpv dataset	Real plant	2624 electroluminescence images (300 × 300 pixels, 8 bit-grayscale), of intact and damaged PV cells with different degradations	[56]	[57–59]
PVWatts calculator	Web tool	Can generate hourly data based on the input PV system's size and location. Can account for losses due to, e.g., soiling, shading, mismatch, etc.	[60]	

2.3. Anomalies and Faults in Wind Turbines

The surveyed literature targets WTs as depicted in Figure 2. The blade–rotor pair converts the wind kinetic energy in a rotation, which is applied to an electric generator via a shaft and a gear box. There are two main types of WTs, namely Vertical-Axis Wind Turbines (VAWTs) and Horizontal-Axis Wind Turbines (HAWTs), as that in Figure 2. HAWTs are the most common and usually consist of two or three blades, or a disc containing several blades. On the other hand, VAWTs are designed with blades of different geometry than those in HAWTs, which rotate vertically to harness wind blowing in any direction.

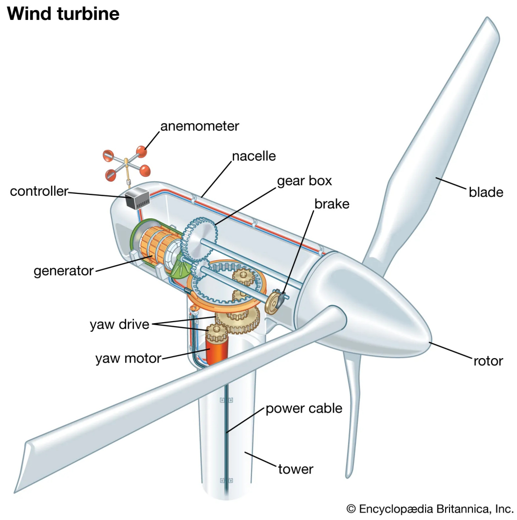

Figure 2. Sketch of a WT [61] (by courtesy of Encyclopædia Britannica, Inc., copyright 2018; used with permission).

Research Highlights

In [62], the authors present statistics about anomalies of the different parts of WTs. It is highlighted that the electrical components, the control system, the pitch system, the blades, and the hub exhibit a higher median failure rate, while the transmission system, the shafts, the bearings, and the structure exhibit a higher median downtime. Failure rates for offshore installations are generally higher than those for onshore installations, mainly because they are subject to rougher operating conditions (e.g., higher wind speed, corrosive action of sea salt, etc.). Downtime in offshore installations is generally higher than that in onshore installations because of logistical aspects.

In general, the technical–scientific literature provides numerous works on WT diagnostic systems [63,64] but provides few details about the different types of faults and anomalies that can occur in WTs (with the exception of [62]). On the contrary, several datasets with real and simulated data are available and listed in Table 3 for reference.

Table 3. Anomaly/fault datasets for WTs.

Dataset Name	Source	Description	References	Related Papers
Wind turbine gearbox monitoring vibration analysis benchmark dataset	Real	Data collected from a functioning gear and a damaged one. The healthy gear was tested only with a dynamometer, while the damaged one was first tested with a dynamometer and then sent to a wind farm for a field test	[65]	
Wind Turbine Blades Fault Diagnosis based on Vibration Dataset Analysis	Real	Uniaxial vibration measurements of a wind turbine operating at various wind speeds. There are three types of issues (blade damage, blade surface degradation, and unbalanced blade) in addition to measurements taken under normal operating conditions	[66]	
Vibration Signals Feature for Fault Diagnosis of wind turbine blade	Real	The Vibration measurements under both normal and fault conditions (blade damage, blade surface degradation, and unbalanced blade)	[67]	
YOLO Annotated Wind Turbine Surface Damage	Real	Surface images of wind turbines with annotated damages	[68]	[69]
Wind turbine fault diagnosis dataset	Real	Measurements from several wind turbines	[70]	[71]
Wind turbine PMSG-Short-Circuit Fault	Simulations	Simulation of a mathematical model at 1 kHz of sampling frequence	[72]	[73]
Vibration and Motor Current Dataset of Rolling Element Bearing Under Varying Speed Conditions for Fault Diagnosis	Real	Dataset containing vibration, current, temperature, and acoustic measurements of a rotating machine. Both normal conditions and malfunctions (e.g., bearing failures at different rotation speeds, shaft misalignment, and rotor imbalance) are considered. It is not directly related to wind turbines but to a rotating machine.	[74–76]	[77]
Gearbox Fault Diagnosis Data	Real	Vibration dataset recorded varying load from 0 to 90% in healthy condition to broken tooth condition	[78]	
EDP Open Data	Real	Historical data of faults occurred in a Wind Farm	[79]	

2.4. Anomalies and Faults in Electrolyzers

In the recent years, the water electrolysis is the most considered way for the eco-friendly hydrogen production, in particular, whereas energy input for the process is achieved by renewable sources. The basic reaction of water electrolysis is expressed in (1), [80].

$$H_2O + Electricity\ (237.0\ \text{kJ mol}^{-1}) + Heat\ (48.6\ \text{kJ mol}^{-1}) \leftrightarrow H_2 + \frac{1}{2}O_2 \quad (1)$$

The electrolyzer is the device where the process is hosted, the main part of which is the electrolytic cell, in which the electrochemical reaction takes place. A typical electrolytic cell representation is reported in Figure 3. From an overall point of view, the cell is composed of two bipolar plates (anodic and cathodic plates), in which the water is fed and at which the electrical potentials are applied. The crucial component of the cell that characterizes the cell typology is the electrolytic membrane, which separates the anodic zone from the cathodic zone, allowing the selective cross-over of a specific ion through it. Moreover, the Gas Distribution Layer (GDL) aims to allow uniform access to the gas from the anodic or cathodic plates towards the membrane. The GDLs terminate with a catalytic layer devoted to promoting the chemical reactions hosted at anodic or cathodic sides. The nature of the catalyst depends on the typology of reaction to be promoted; for example, in a Polymeric Electrolyte Membrane (PEM) electrolyzer, at the anodic side, catalysts based on ruthenium and iridium are widely used [81] to promote the water splitting into H^+ protons and OH^- anions, while at cathodic side platinum nanoparticles (dispersed on carbon supports) are mainly employed to promote the reduction of the proton to hydrogen [82].

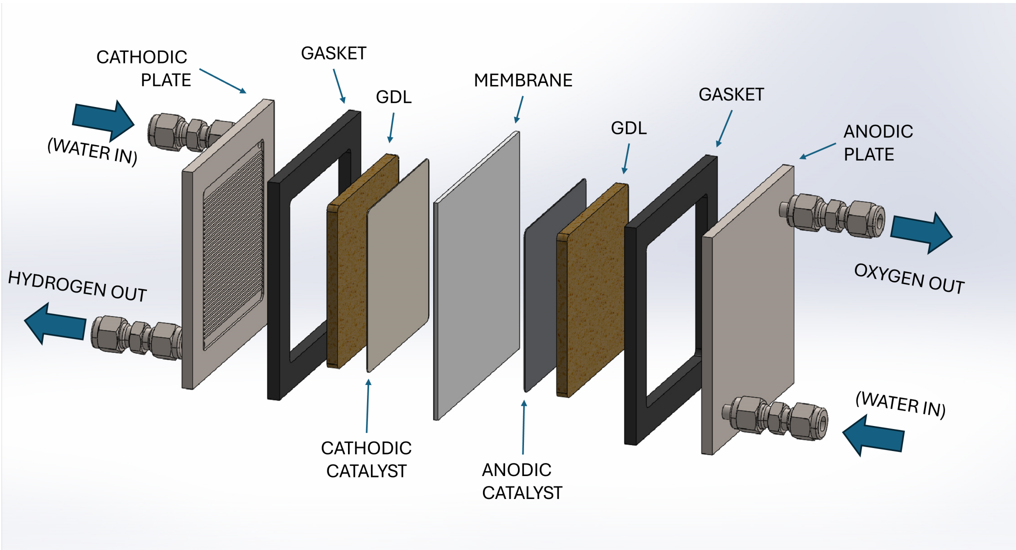

Figure 3. Sketch of a PEM electrolyzer.

Research Highlights

The survey's outcome is summarized in Table 4. Notably, the analysis reveals that predominant failure causes are associated with the membrane and catalyst, with occurrences of failures in bipolar plates and current collectors being comparatively infrequent. Membrane failures are typically associated with aging and cracking mainly due to fabrication defects or due to thermal, mechanical and chemical stresses in normal and severe operating conditions. Mechanical failures, including cracking, perforation or pinholes, are due to abnormal stresses or other mechanical factors, such as temperature, humidity, start-up and shut-down cycles, operating conditions fluctuation and warm-up/cool-down procedures [83]. Temperature anomalies could increase membrane failure rate up to 2 order of magnitude when operating T increases from 55 °C to 150 °C [80]. Impurities could also result in membrane degradation [84,85], often due to catalyst corrosion [86]. Moreover, radical attacks are responsible for membrane degradation [80]: the phenomenon is more promoted for low current density [87,88] since a faster membrane thinning could be observed [89]. It is, however, worth noting that the temperature effect is more severe with respect to the operative current density [88]. Catalyst degradation is a very slow process and thus is not responsible for sudden cell failure. Among typical catalyst deactivation mechanisms, the most common are particle dissolution and migration, sintering, catalytic layer detachment and support passivation [90]. A more common phenomenon is the catalytic particle dissolution and the consequent penetration in the membrane lattice, affecting its functionality [80,86]. Another mechanism is the catalyst passivation, due to the oxidation of the catalytic support at the anodic side, thus reducing the electron flux between support and the anodic plate. One of the most common deactivation mechanisms is the catalyst sintering, since high temperature could cause the catalytic particle agglomeration, resulting in a reduced catalytic activity [91]. Finally, catalytic poisoning due to impurities in the water or metallic dissolution in bipolar plates is responsible for a (more or less) transitory catalytic deactivation, since impurities occupy active sites [92]. Diverse diagnostic approaches are deployed, with the most cutting-edge methodologies involving statistical techniques grounded in neural networks. These, however, necessitate extensive historical or synthetic device data, leading to prolonged characterization times. In contrast, conventional methods relying on electrical and electrochemical measurements, while more practicable, exhibit a more confined capacity for fault identification.

Table 4. Main contributions on anomalies/faults in electrolyzers.

Target Component	Description	Cause	References
Membrane	Mechanical degradation	Current collector hole; Widening and narrowing; Non-uniform hydration; Lack of water	[83,85]
	Thermal degradation	Thermal stresses; Thermal cycles	
	Chemical and electrochemical degradation	Contamination; Radical attacks	
Catalysts	Dissolution	Too high potential; Formation of soluble iridium complexes during the oxygen evolution reactions; Current inversion in the shut-off procedure	[84,86,92]
	Support passivation	Too high potential; Highly oxidant environment	
	Agglomeration	Sinterning of active sites; Start-up and shut-down load cycles	
	Ionomer dissolution	High current density, radical chemical attack	
	Cations contamination	Locking of active sites for potential deposition; Replacement of protons in ionomer by cations	
	Mechanical damages	Non-uniform tightening pressure; Non-uniform membrane dilatation	
Bipolar plates	Embrittlement for hydrogen	Hydrogen adsorption by cathodic metallic plates	[86,93]
	Passivation	Oxide layer formation	
	Corrosion	Titanium oxidation; Iron corrosion by acids	
Current collectors	Chemical embrittlement	Metallic plates passivation and corrosion	[94]
	Mechanical embrittlement	Non regular compression; Hydrogen embrittlement	

The investigation of possible empirical datasets pertaining to electrolyzer failures highlighted a consistent lack in this regard. For this reason, Table 5 actually compiles only mathematical models that can be used to achieve synthetic datasets anyway.

Table 5. Anomalies/faults models for electrolyzers.

Target Phoenomenon	Typology	Description	References
Membrane degradation	Predictive mathematical model of membrane degradation	The model accounts for the load cycle degradation mechanism	[95]
	Predictive mathematical model of cell performances based on temperature and load	The model accounts for the degradation mechanism based on radical attack to the membrane. The degradation curve depends by cell temperature and load	[87]
	Predictive mathematical model of membrane thinning	The model accounts for the degradation curve depending on cell temperature and load	[87]

2.5. Anomalies and Faults in Fuel Cells

A FC is a device able to generate electricity by exploiting electrochemical potential of oxidation-reduction reactions. In a general overview, reactants are basically a fuel and an oxidant: in particular in the case the fuel is the hydrogen, and the oxidant is oxygen (or air), the reaction, summarized in (2), is able to generate electrical power and heat, by resulting in water as the only side-product.

$$H_2 + \frac{1}{2}O_2 \leftrightarrow H_2O + Electricity + Heat \quad (2)$$

Of course, depending on the employed FC typology, methane, ethanol, carbon monoxide or other hydrocarbons can be used as fuel and carbon dioxide can be used as an oxidant. From a global point of view, a FC is an electrolytical cell (similar to cells used in electrolysis) able to intercept electrons involved in the oxidation-reduction reactions, thus forcing electrons to flux in an electrical circuit, thus generating electrical power. FC elements are reported in Figure 4. The main components of the cell are the same as already described for the electrolyzer: fuel is fed to the cathodic plate, while an oxidant is fed to the anodic plate; bipolar plates also act as electrical collectors. Reactants are delivered to the catalytic layers through a dedicated gas distribution layer; on the catalytic surface, the chemical reactions take place, which strictly depends on the cell typology. The membrane separating anodic and cathodic sides acts as a selective barrier, aiming at the cross-over of only a selected ion depending on the hosted process: in the case of PEM-FC, the membrane only allows the proton (H^+) crossing.

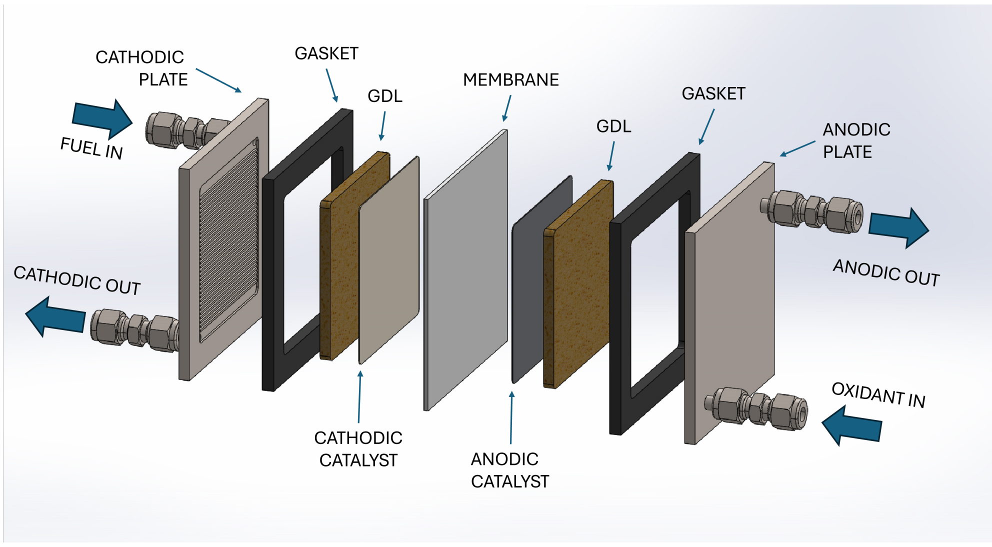

Figure 4. Sketch of a PEM-FC.

Research Highlights

The survey's outcome is summarized in Table 6 and shows that the most fragile components are the membrane and the catalyst, accounting for 95% of malfunctions. As mentioned for the electrolyzers, membranes can suffer from cracking or perforation due to uncontrolled humidity or temperature in the process which originates from tensile, mechanical and thermal stresses responsible for the failure of the component [96,97], causing the reactant's crossover and in turn the uncontrolled fuel combustion [98]. It is worth underlining that such events are more frequent in the early period of the cell lifetime [99]. Membrane degradation can moreover be originated by peroxyl and hydroxyl radicals attack, particularly in low current conditions: under such conditions, PEM membrane could release fluorides, thus undergoing a weakening that leads to the membrane failure [100,101]. The second reason for FC failure is catalyst degradation, which could occur for particle sintering [102], carbon monoxide poisoning (for PEM FCs) [103] or carbon support oxidation [104]; these failure mechanisms are responsible for a more or less severe activity reduction of the device, rather than a real cell service interruption. Some phenomena such as corrosion or mechanical stresses could occur also at the GDL [103] and bipolar plates [101] causing conductivity loss and structure deformation or fracture. GDL can also suffer from embrittlement of the support material due to severe operating conditions as well as to the contact with hydrogen. Finally, inadequate operating conditions, in terms of temperature or pressure, as well as factory defects, can be responsible for sealing failure originating from mechanical fractures [101].

Table 6. Main contributions on anomalies/faults in FCs.

Target Component	Description	Cause	References
Membrane	Mechanical degradation	Mechanical stresses due to non-uniform pressure in assembling procedure; Non-uniform humidification; Catalyst penetration in the membrane; Sealing material traces	[97,98,101,105–107]
	Thermal degardation	Thermal stresses and cycles	
	Chemical and electrochemical degradation	Contamination; Radical attacks	
Electrodes	Activation loss	Catalyst sintering and unsoldering	[102,105,107–109]
	Conductivity loss	Catalytic support corrosion	
	Reactants mass transport efficiency loss	Mechanical stresses	
	Reduction in tolerance to reactants	Contamination	
		Materials hydrophobicity variation due to Nafion or PTFE dissolution	
GDL	Structure reduction	Support material embitterment; Carbon layer corrosion	[103]
	Water management ability reduction	Mechanical stresses; Materials hydrophobicity variation	
	Conductivity loss	Corrosion	
Bipolar plate	Conductivity loss	Corrosion; Formation of a resistant surface layer	[101]
	Fracture/deformation	Mechanical stresses; Thermal cycles	
Seals (gaskets)	Mechanical fractures	Corrosion; Thermal stresses	[101]

Unfortunately, it was not possible to obtain experimental data on faults associated with FCs. Conversely, several methods for FC failure prediction were explored in the available literature, both stochastic [110,111] and neural network-based [112,113]. Their usage is strictly connected to the achieving of instrument-typical data through a long training phase. Analytic methods require the knowledge of specific FC parameters, which is not easy to obtain [113]. Several techniques for online failure analysis and characterization are available in the literature: among them, the most viable are the Electrochemical Impedance Spectrometry (EIS) [108], the V/P characteristic curve analysis [114], and the cell voltage measuring [115]. Several mathematical models able to describe the degradation mechanism are reported in Table 7.

Table 7. Anomaly/fault models for FCs.

Target Phoenomenon	Typology	Description	References
Membrane degradation	Predictive mathematical model of membrane degradation	The proposed method is validated against polarization mechanisms due to over-current and over-voltage phenomena. The approach is based on finite elements method	[107]
	Predictive mathematical model of membrane degradation	The semi-empirical model accounts for the current losses, catalyst polarization and ohmic resistance	[116]
	Predictive mathematical model of membrane degradation	The model accounts for polarization resistance as the sum of all polarization losses	[117]
Catalyst degradation	Predictive mathematical model of catalyst dissolution	The model is based on catalyst transformation theory	[118]
	Predictive mathematical model of catalyst dissolution	The model accounts for several phenomena determining the catalyst deactivation	[109]
	Predictive mathematical model of catalyst dispersion and sintering	The model analyzes, at cathode-side, the platinum-based catalyst dispersion and agglomeration phenomena, leading to catalytic activity reduction	[119]
Stack potential degradation	Mathematical model of stack potential decay	The model determines the stack potential decay equation and the multiplicative factors based on start/stop, IDLE and over-potential phenomena	[120]

2.6. Anomalies and Faults in Battery Systems

Given the large number of BS technologies available, which would be impractical to address, we restricted this survey to Lithium-ion (Li-ion) based BSs, which currently are the most widespread [121]. Figure 5 shows a sketch of a Li-ion battery cell with the four main components highlighted: the positive electrode, negative electrode, electrolyte and separator. The green and purple areas indicate the active materials in the corresponding electrodes, and the red and blue items indicate the electrolyte with the additives and binders, respectively. The separator isolates the two electrodes to avoid internal short circuits, and it is realized with a porous material to allow, along with the electrolyte, the ions transport.

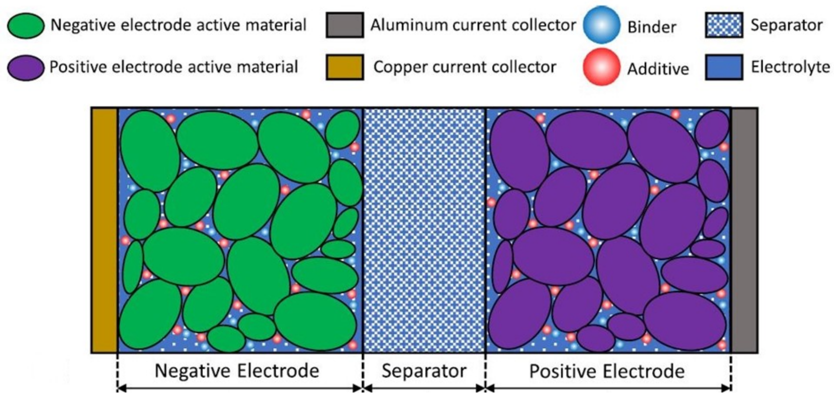

Figure 5. Sketch of a Li-ion battery cell (adapted from [122]).

Research Highlights

The survey's findings are gathered in Table 8. The outcomes shown in Table 8 highlight that the BS faults can be classified into two types [123]: cell faults and system faults.

The cell faults are mainly caused by battery degradation and include loss of active material; electrolyte consumption; increase in internal resistance; lithium deposition; gas generation; Solid Electrolyte Interphase (SEI) thickening. A passivation layer called SEI is formed on electrode surfaces from the decomposition products of electrolytes. The SEI allows Li^+ transport, blocks electrons in order to prevent further electrolyte decomposition and ensures continued electrochemical reactions [124]; current collector corrosion; internal short circuits (can cause an explosion and is mainly caused by overload); thermal runaway; capacity diving; liquid leakage.

The system faults are mainly caused by the battery management system anomalies/-faults [125,126], sensory system anomalies/faults, cables and connections anomalies/faults. In turn, they can be classified as overcharge (can provoke the reaction of the positive electrode with the electrolyte, resulting in heat generation, pressure increase, and subsequent fire); overdischarge; reduced battery life; thermal runaway; reduced battery performance; equalization errors; thermal runaway accident; increase in internal resistance; thermal runaway safety accident.

Finally, Table 9 reports the main datasets related to faults in Li-ion BSs.

Table 8. Anomalies/faults for BSs.

Target Component	Description	Cause	References
Cell	Loss of active material	Battery degradation	[127]
	Electrolyte consumption		[128]
	Increase in internal resistance		[129]
	Lithium deposition		[130]
	Gas generation		[123]
	SEI thickening		[124]
	Current collector corrosion		[131]
	Internal short circuits		[132]
	Thermal runaway		[133]
	Capacity diving		[123]
	Liquid leakage		[123]
System	Overcharge	Battery management system anomaly/fault	[134]
	Overdischarge		[135]
	Reduced battery life		[136]
	Thermal runaway		[133]
	Reduced battery performance	Sensory system	[136]
	Equalization errors		[123]
	Reduced battery life		[136]
	Thermal runaway accidents		[133]
	Increase internal resistance	Cables and connections	[129]
	Thermal runaway safety accidents		[133]

Table 9. Anomaly/fault datasets for BSs (adapted from [137]).

Dataset Name	Source	Description	References	Related Papers
NASA Data Repository	Lab testing	Data sets suitable to develop algorithms useful as prognostic tools	[138]	
IEEE Data Port	Simulations	Data set obtained by simulating a lithium polymer cell model ePLB C020, with an effective capacity of 15 Ah, related an electric car	[139]	
Stanford Fast Charging Datasets	Lab testing	Dataset obtained through tests performed on commercial lithium-ion batteries under fast charging conditions. In particular, the cells, of the lithium-iron-phosphate (LFP)/graphite type, produced by A123 Systems (APR18650M1A), were tested on a 48-channel Arbin LBT device. The cells considered are characterized by a nominal capacity of 1.1 Ah and a nominal voltage of 3.3 V	[140]	[141]
Lifecycle Prediction Dataset	Lab testing	Data set obtained by testing commercial lithium-ion batteries under fast charging conditions. The lithium-ion phosphate (LFP)/graphite cells, manufactured by A123 Systems (APR18650M1A), were tested using the 48-channel Arbin LBT device in a forced convection temperature chamber set to 30 °C. The cells have a nominal capacity of 1.1 Ah and a nominal voltage of 3.3 V	[142]	[143]
University of Wisconsin Madison	Lab testing	Operational dataset for the Panasonic 18650PF lithium-ion battery	[144]	[145]
BEEPt	Lab testing	Set of tools designed to support Battery Evaluation and Early Prediction of life cycle corresponding to the research of the d3batt program and the Toyota Research Institute	[146]	[147]
Universal Battery Database	Lab testing	Open source Li-ion data management and modelling software	[148]	
Alawa-toolbox	Lab testing and simulations	Dataset from University of Hawaii, which provides a large number of curves with different degradation modes, LLI and LAM	[149]	[150]

2.7. *Anomalies and Faults in DC/x Conversion Systems*

Power electronics converters are circuits to adequately interface a power source with an electricity absorbing system, such as a load, a storage or a sinking busbar of the main grid. They are used to implement DC/x conversion systems and are typically realized with different stages, as Figure 6 shows. The stages include input and output filters and switching and magnetic sections. The switching section is the converter's main part which can be realized by Metal–Oxide–Semiconductor Field-Effect Transistors (MOSFETs) or IGBTs. A gate driver circuit is required to turn on/off the switchings according to Pulse-Width Modulation (PWM) techniques.

DC/DC converters are sourced by an input DC source to provide a different voltage level at their output terminals. On the other side, DC/AC converters can take advantage of an input DC source to provide output AC waveforms. Both DC/DC and DC/AC converters can enable unidirectional or bidirectional power flows.

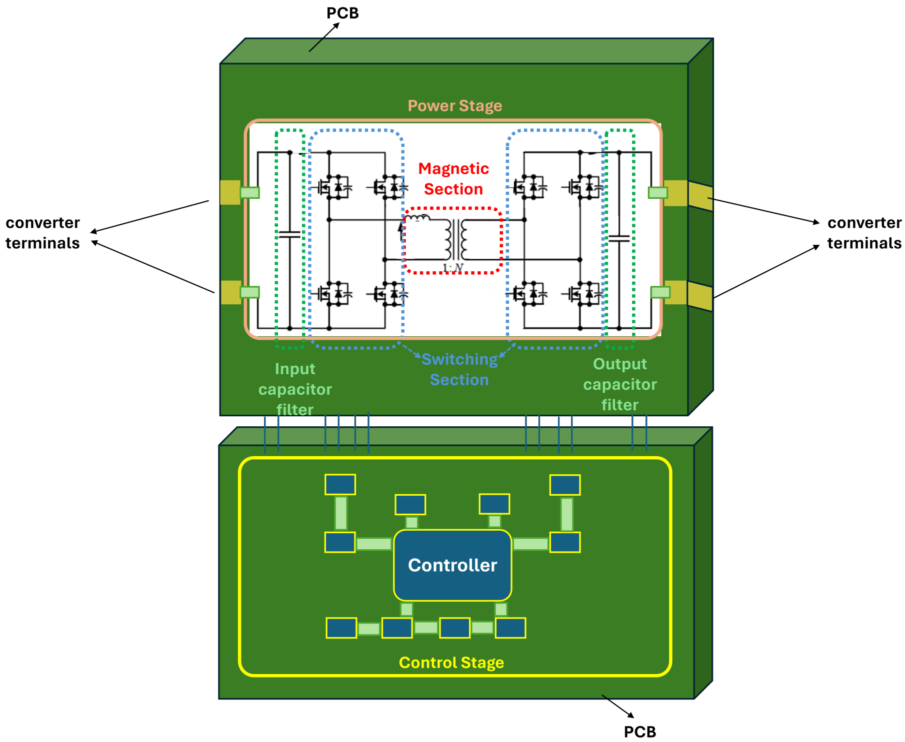

Figure 6. Sketch of a DC/x conversion system.

Research Highlights

The surveyed literature highlights that converters might be subject to operating conditions that can be widely varying over time. As a consequence, their components are subject to electrical, thermal, mechanical or combined (electro-thermal, etc.) stresses. Converter performances are additionally impacted by aging. These causes produce anomalies and/or faults to the power stage devices, the control stage, the driving circuits of the switching components, and the converter inputs and outputs terminals.

Mainly, the sector literature focuses on the anomaly/fault physics of individual components, also reporting most subject to anomalies/faults.

In switching devices, overcurrents and overvoltages can cause overtemperature and thus thermal stress. In turn, this can have significant effects on secondary breakdown phenomena, which can determine the switching devices destruction. Therefore, at the power converter design stage, it is essential to consider the switches Safe Operating Area (SOA) and the use of appropriate heat sinks. Additionally, also environmental conditions must be included in the design since the junction temperature T_j depends on the ambient temperature T_a according to

$$T_j = T_a + P_a\, R_{T_{j-a}}, \tag{3}$$

where P_a is the power loss, and $R_{T_{j-a}}$ is the ambient-junction thermal resistance.

The dependence on the junction temperature characterize also the Drain–Source resistance, Gate–Source voltage, and switch threshold voltage V_{th}. The Drain–Source resistance increases to the junction temperature growth (Figure 7a), the Gate–Source voltage decreases to the junction temperature rise (Figure 7b), and V_{th} decreases to the ambient temperature increase (Figure 8). In particular, the latter aspect is crucial since the temperature rise and the increase in the number of heat waves in the future will increase the probability of unwanted switching, with harmful consequences for the individual component and the DC/x conversion systems they are used in.

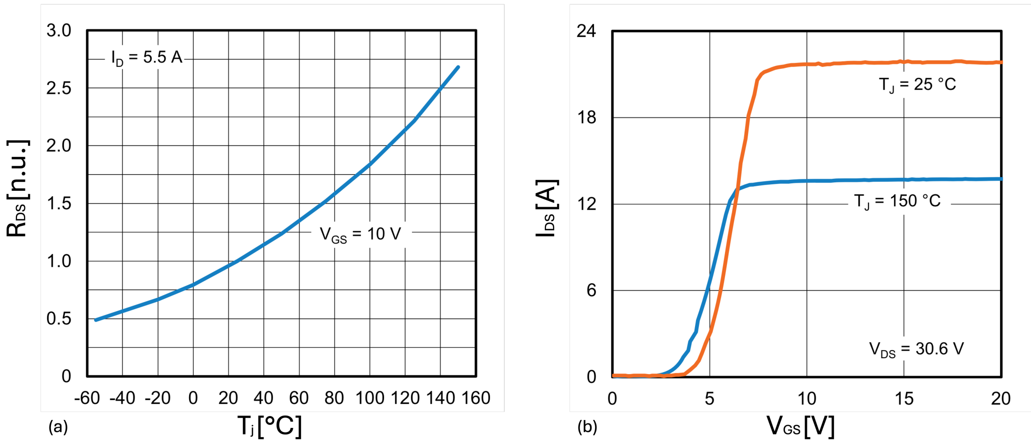

Figure 7. (**a**) Drain–Source resistance vs. junction temperature (“n.u.” stands for “normalized units”); (**b**) Drain–Source for different junction temperatures [151].

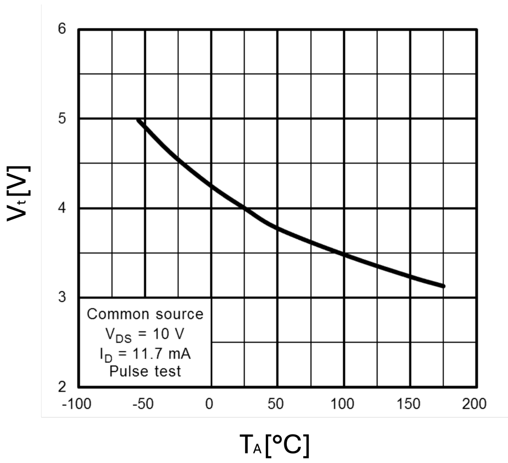

Figure 8. Typical threshold voltage vs. ambient temperature in MOSFETs [152].

Thermal stress can degrade also the mechanical properties of the material that realizes the switching devices. The use of materials with different thermal expansion and compression can, in fact, cause cracks with the consequent failure of the switches materials. Finally, further anomalies/faults caused in switching devices are electrostatic discharges, leading the gate oxide to break without immediate malfunctions for the component. Delayed anomalies/faults can instead be determined, which therefore are difficult to trace back to their initial cause. A mitigation strategy consists of the adoption of suitable protections and the monitoring of the gate charge through appropriate additional circuitry.

With reference to capacitive components, electrolytic, ceramic and film capacitors are used in interface converters. They feature temperature-dependent capacity, as shown in Figure 9, and their operative life (in hours) halves every 10 °C of temperature increase, as reported in Figure 10.

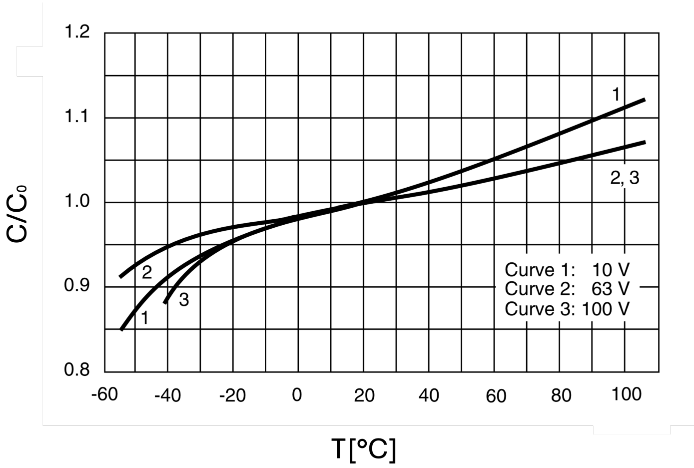

Figure 9. Typical capacitance (normalized against values at 20 °C, 100 Hz) vs. temperature characteristics in electrolytic capacitors [153].

Finally, anomalies/faults may be determined in driver circuits that are required to appropriately switch on/off the switching devices via the provision/recovery of a suitable amount of gate charge, synchronized by the control algorithms embedded into the DC/x conversion systems. In particular, the driver's performance is negatively impacted by unwanted negative voltages at their input/output. These are produced mainly by the on/off switching transients of the converter's MOSFETs/IGBTs (Figure 11) , in combination with high-order effects usually modeled as parasitic capacitances and inductances.

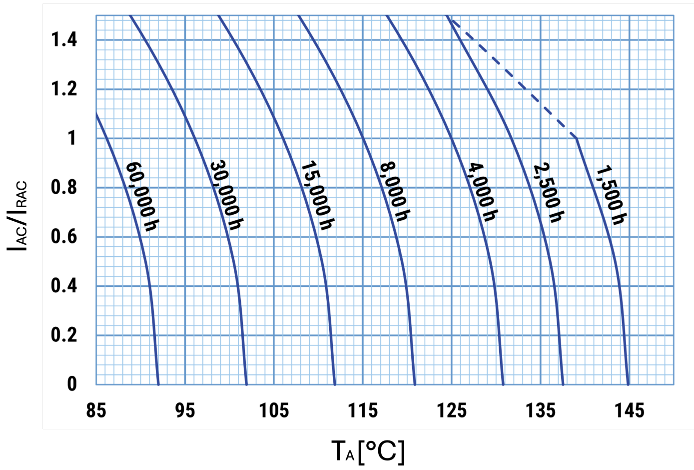

Figure 10. Typical ripple current (normalized against the maximum value) and operative life vs. temperature characteristics in electrolytic capacitors [154].

In summary, the survey on anomalies/faults in DC/x conversion systems resulted in the literature reported in Table 10, while no related datasets were found in all cases, i.e., in case of the interface converters, the switching, capacitive and inductive components, and the control stage.

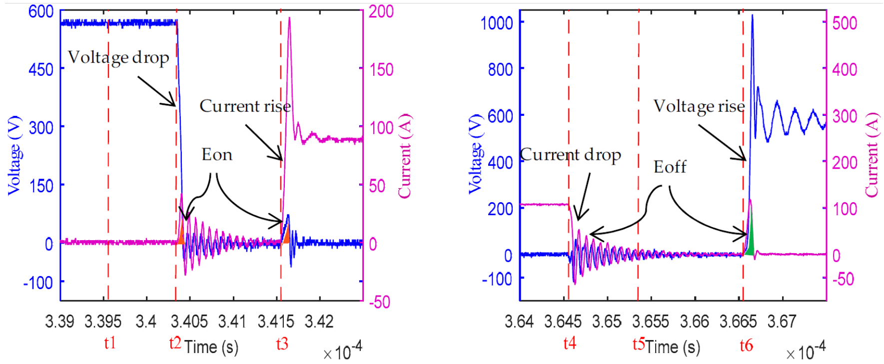

Figure 11. Typical MOSFETs/IGBTs turn on (**left**) and turn off (**right**) characteristics [155].

Table 10. Main contributions on anomalies/faults in DC/x conversion systems.

Target Component	Description	Cause	References
Magnetic/ capacitive/ switchingdevices	Switches damage	Thermal stress	[156]
	Capacitor damage	Electrical stress	[157]
	Inductor damage	Thermal and electrical stress	[158]
Printed circuit board	Delamination Cracks Weld deterioration	Aging	[159]
Converter terminals	Power stage devices overcurrent and overtemperature	Terminals short-circuit	[160]
Converter power stage	Ground fault	Worn, frayed, or damaged insulation due to mechanical, environmental, electrical stressing	[160]

2.8. Anomalies and Faults in Monitoring Systems

A monitoring system can be briefly broken down into sensors, wirings and a user interface, as shown in Figure 12. Typically, a software layer manages the data transmitted by the sensors and presents them to the user via the interface. However, the sensors are the main components affected by anomalies/faults, and the survey is restricted to them.

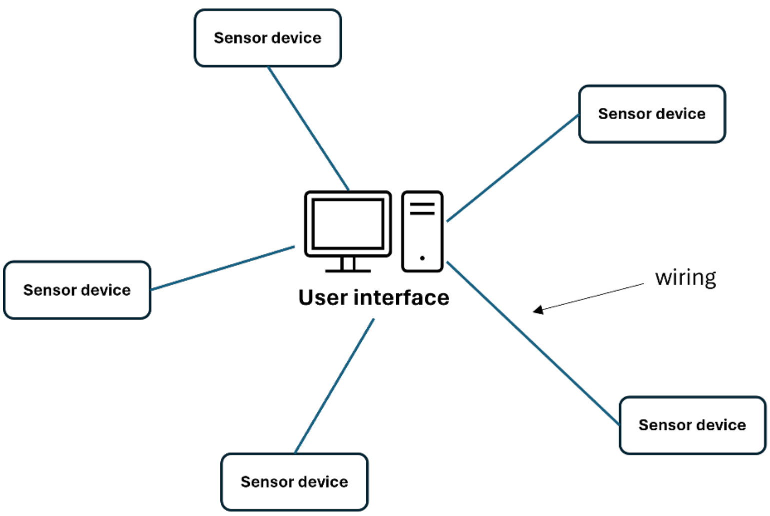

Figure 12. Sketch of a monitoring system.

Research Highlights

The surveyed literature is organized in Table 11. It is highlighted that the main anomalies/faults the sensors are subject can be listed as mechanical [161], that affects the enclosure (e.g., due to the degradation of materials [162], vibrations, external shocks [163]), electrical, that affects the electrical properties of the devices (e.g., loss of insulation [164,165], anomalous measurement residual [166] due to blackout or overloading of the device) and other, that affects the measurements, such as, e.g., those due to noise [167], reading errors (value read by the device different from the actual one due to a change in gain) [168], calibration losses or performance degradation [169].

The survey highlights that the main causes of failures/faults of the sensors derive from their operating conditions and the environment they are deployed in. The most common are reading errors due to incorrect calibration, performance degradation, or electrical faults; mechanical anomalies/faults are less frequent.

Regarding datasets, it was not possible to find any targeting the specific sector of electricity networks (smart meters).

Table 11. Main contributions on anomalies/faults in monitoring systems.

Target Component	Description	Cause	References
Sensor	Performance degradation	Mechanical degradation	[162]
		Vibrations and/or external shocks	[163]
	Electrical fault	Loss of electrical insulation	[164,165]
		Anomalous measurement residual	[166]
	Wrong data	Noise	[167]
		Gain changing	[168]
		Loss of calibration	[169]

2.9. Anomalies and Faults in Communication Systems

Figure 13 shows a simple scheme of a communication system, which has the main aim of enabling data transmission and recovery across an unreliable channel. Briefly, a communication system consists of a sender, a receiver and a communication support.

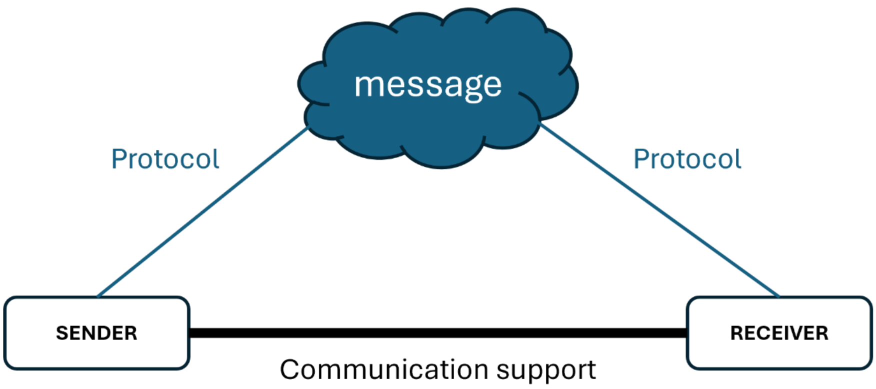

Figure 13. Sketch of a communication system.

The data are arranged in messages by means of a suitable protocol stack, depending on the particular application considered. Therefore, the causes of failure depend on multiple subsystems, as described in the following.

Research Highlights

The surveyed literature is organized in Table 12. The study has highlighted that the main anomalies/faults associated with communication systems can be classified [170] into failures of the communication support regarding the support and transmission medium (e.g., fiber breakage, excessive bending, connectors or splice breakage [171,172]), receiver failure involving a malfunction of the receiver, such as a high data packet reception time [173,174] and data integrity that affects the integrity of the transferred data, degrading the accuracy and reliability of the transmission, and caused by alteration or loss of part of the transmitted data packet [175]. These last are, generally, recognized by the receiver using checksum [176].

Data integrity is a central aspect in cyber–physical systems (as the future renewable-based power systems will be) and including possible anomalies/faults in this survey would be impractical due to the vastness of the domain. However, the reader is referred to [177] where it is highlighted that it can be compromised also by a wide range of cyber-attacks, necessitating an adequate countermeasure. Indeed, categories of cyber-attacks such as spoofing, malware, denial of service, man-in-the-middle, replay attacks, and backdoors can undermine the confidentiality, integrity, availability, and accountability of data. Effective countermeasures include the use of secure communication protocol (e.g., secure DNP3, PKI, TLS, SSL, Encryption) or authentication methods, data loss prevention techniques and automated security compliance checks, using AI, to continually check systems for compliance.

Summarizing, the survey has highlighted that failures due to the support medium are more frequent than the other two types. For all types of faults, it was not possible to find simulated/experimental datasets but only methods for fault diagnostics (Table 12).

Table 12. Main contributions on anomalies/faults in communication systems.

Target Component	Description	Cause	References
Communication support	Total or partial loss or alteration of the transmitted data packet	Support and transmission medium fault	[171,172,175]
Receiver	Receiver faults	Malfunction of the receiver, long data packet reception time	[173,174,176]

3. Conclusions

This paper presents a survey of anomalies and faults targeting the main technologies of future renewable-based power systems that may impact their reliability. The survey compiles the literature findings and relevant datasets that can be used for further investigation, in corresponding tables for conciseness. With regards to similar papers, this paper includes many technologies and does not restrict itself only to one specific one. For instance, beyond technologies limited to the power domain, monitoring and communication systems are surveyed. This can help other researchers in orienting their research effort via a unique entry-point and self-consistent reference.

Regarding the findings, many gaps are highlighted, thus realizing possible future research directions, namely the lack of a common taxonomy that prevents the establishment of a structured knowledge on the topic, a lack of contributions on anomalies/faults specific to wind turbines, a lack of datasets related to electrolyzers, fuel cells, DC/x conversion, monitoring and communication systems. Further, in the case of monitoring and communication systems, the scientific literature is very dated, and therefore does not consider possible new aspects that would be currently worthy of investigation, and is not oriented to the domain addressed, thus considering peculiar aspects that are instead left out.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
BS	Battery System
EIS	Electrochemical Impedance Spectrometry
FC	Fuel Cell
GDL	Gas Distribution Layer
HAWT	Horizontal-Axis Wind Turbine
IGBT	Insulated-Gate Bipolar Transistor
LAM	Loss of Active Material
Li-ion	Lithium-ion
LLI	Loss of Lithyum Inventory
ML	Machine Learning
MOSFET	Metal–Oxide–Semiconductor Field-Effect Transistor
MPPT	Maximum Power Point Tracking
PEM	Polymeric Electrolyte Membrane
PV	Photo Voltaic
PWM	Pulse-Width Modulation/Modulated
SEI	Solid Electrolyte Interphase
STC	Standard Test Condition
VAWT	Vertical-Axis Wind Turbine
WT	Wind Turbine

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