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Abstract: The decarbonization of the electricity grid as one among the actions to reduce fossil fuel emissions, and thus their impact on global warming in the future, will be achieved mainly via the integration and widespread diffusion of renewable power sources. This is going to be supported also by the shift from the paradigm 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 reduce the reliability of the grid very likely, unless appropriate countermeasures are taken/implemented, hopefully at the same time the paradigm shift is being achieved. To this aim, it is important to identify the anomalies and main fault causes that might determine in renewable-based power systems. This paper surveys the current state-of-the-art on anomalies and faults affecting wind-PV-storage hybrid power systems, i.e., the main renewable technology ensemble that will establish the future grid, and highlights possible research directions that may help to fill the literature gaps.

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

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1. Introduction

The reduction of 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

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entire technological mix and beyond (i.e., namely, the conversion, monitoring and communication systems).

For instance, [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 nor the survey is 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 it is not the main target. Power systems are addressed by the review in [3] however only related to the electric part, while the article we propose reviews anomalies and faults that affect, e.g., also the communication systems in renewable-based power systems. In this regard, [3] does not specifically consider anomalies and faults, nor renewable energy and generally targets ML applications in power systems. Renewable-based power systems are also addressed in [4], however with the scope being restricted to those with a dominance of inverter and targeting cybersecurity instead of anomalies and faults in general. A survey on fault diagnosis in micro-grids can be found in [5], thus it does not generally address power systems, renewable energy, and anomalies and faults; also it is not recent since it dates back to 2016. The same authors have already proposed a similar contribution in 2014 [6], addressing faults and fault diagnosis. However, also this case move 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-grid is presented. But, the focus is not on renewable-based power systems. The paper [8] does not focus on a unique system and addresses PV and WT renewable generation. However, for instance it does not include the hydrogen-related technologies, as instead this paper does, and in particular, 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 the future power systems. Furthermore, [8] restrict its review to 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, 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 with respect to what is proposed in this paper, and with the renewable generation not being considered at all.

Summarizing, the analyzed literature is either too specific, by restricting the investigation on particular instances of power systems (e.g., PV systems, district heating substations), with peculiar implemented software (e.g., AI) and hardware (e.g., inverter) technologies, and aim (e.g., fault location), and do not broadly gather 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 considers them even within similar frameworks to that identified by this paper are basically missing.

The paper is organized according to the standard format of this journal, and the rest is 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

The present article elucidates the primary causes of anomalous behaviors and malfunctions in specific systems, along with the accessibility of data for their characterization. To achieve this objective,

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technical-scientific literature and technical documentation (e.g., datasheets provided by manufacturers) for each relevant component has been systematically examined. This process aimed to identify the most prevalent types of malfunctions and the availability of simulated and/or experimental data for their characterization. In instances where such data was not readily available, a thorough exploration of mathematical models and/or empirical/simulative methodologies suitable for fault characterization has been conducted. To enhance the usability of the obtained results, they have been organized into tables.

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 about. This is well reflected in how the subject is addressed by, e.g., IEEE and NASA, two prominent institution 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 use both interchangeably [14], in what follows, the same convention is kept without any further discussion. Yet, 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 fellows.

2.2. Anomalies and Faults in PV Systems

The survey focused on articles related to PV systems (as shown in Figure 1), composed by several PV modules organized in strings in diverse configurations. The DC power generated by the photovoltaic array is directed towards the DC/DC converter. The voltage and current readings are continuously monitored and adjusted within the Maximum Power Point Tracking (MPPT) to maximize the output power. Subsequently, the output from the DC/DC converter is sent to the DC/AC inverter and then to the grid (for grid-connected PV systems). Prior to entering the grid, the inverter's output is directed through a low-pass filter leaving only the fundamental frequency of the utility grid (typically 50 Hz or 60 Hz). Filtered signal then passes through a step-up transformer before being injected into the utility grid. Sometimes, an electricity storage is also paired, whilst this is neglected since it is separately addressed in the following sections.

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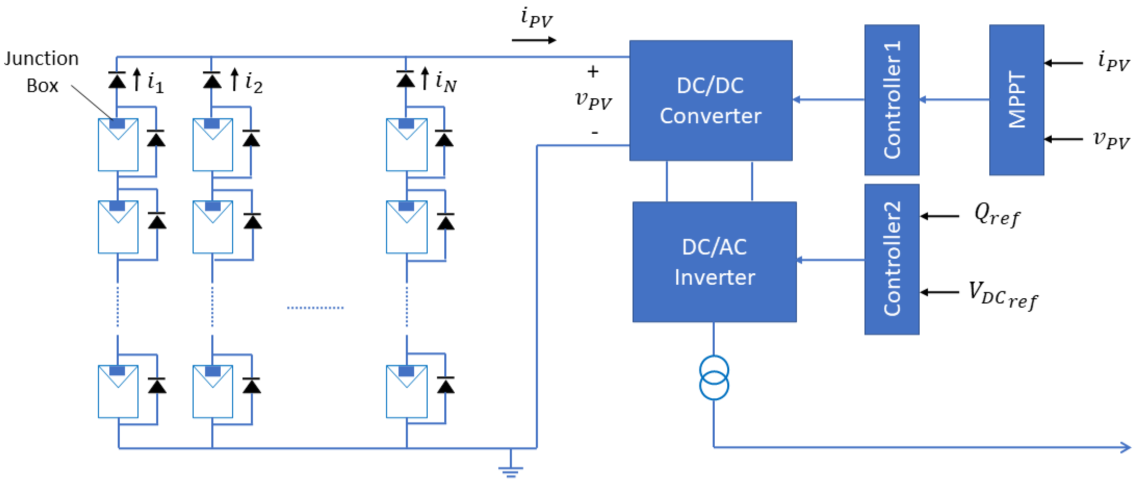

Figure 1. Sketch of a PV system (adapted from [15]).

2.2.1. 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. Authors of [16] groups PV anomalies and faults in 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 circuit, bridging, fault to bypass diode and open circuit [17–19]. The main causes of these type of faults are manufacturer's defects, subpar fabrication quality, packaging inadequacies, and improper wiring and have a dramatic impact on PV system. In particular: short circuit entails the failure to supply power to the DC load or the power conditioning unit; bridging results in a complete absence of power output; bypass diode fault manifests as an incapacity to mitigate hotspot events; open circuit fault leads to the incapability of delivering power to the DC load or the power conditioning unit leading to a partial blackout or to a not homogeneity in the power production [16].

The external anomalies and faults are located outside the PV module and usually are due to the environmental condition, natural disasters but also to wrong packaging, installation, etc. Since PV systems are located outdoors, they frequently encounter environmental stress as high temperatures, rain, snow, and the PV system does not operate under Standard Test Conditions (STCs), thus failing to achieve their nominal power. 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, and overhead power lines, etc. [22,23]. Additionally, environmental factors such as dust accumulation, bird and leaf droppings could lead to a partial shading condition [24,25]. Furthermore, natural disasters like lightning and storms [26] can have dramatic consequences on the PV modules. Some of the faults listed before are temporary because they are reversible (e.g., partial shading, dust accumulation, etc.). Permanent mismatch faults, instead, are irreversible and can be related to 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

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very diverse the severity of the related damages vary as well, going from a non homogeneous power production to a complete blackout [16].

The electrical faults are related to the perturbations to variables as voltage, current, power, etc. The main electrical faults are the ground faults, line-to-line fault, and arc fault [29,30]. These faults can have dramatic consequences as electrocution of operators or great damage to the equipment as a 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 literature findings about the other systems addressed by this paper, are organized with equal 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]

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	Cell breakage	Multiple (production, transport, installation, vibrations, environmental stress, improper cleaning, and maintenance, etc.)	[27], [39]
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], [18], [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 installation or others, the third column describes the dataset, the fourth column reports the bibliografic 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 datased of the other systems addressed by this paper, are organized with equal column names.

Table 2. Anomalies/faults 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]

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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]
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 of 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 (300x300 pixels, 8 bit-grayscale), of intact and damaged PV cells with different degradations	[56]	[57], [58], [59]

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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 blades transform the kinetic energy of the wind in a rotation movement applied to the rotor and, through a generator, in electricity. There are two main types of WTs, Vertical-Axis Wind Turbines (VAWTs) and Horizontal-Axis Wind Turbines (HAWTs) as the one described 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 that rotate around a vertical axis, thus being able to harness wind blowing from any direction.

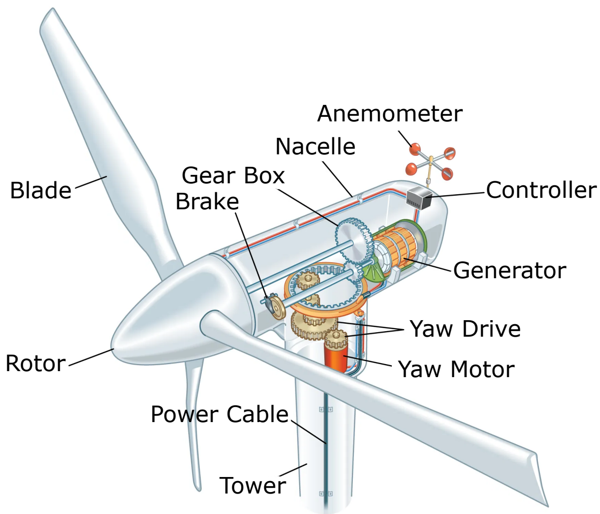

Figure 2. Sketch of a WT (adapted from [61]).

2.3.1. Research Highlights

In [62] authors present several statistics of anomalies of different constituting components of the WT. Some of them have a higher median failure rate (electrical components, control system, pitch system, blades, hub), while others have a higher median downtime (transmission, system, shafts, bearings, structure). Failure rates for offshore installations are generally higher than those for onshore installations, even because they are under more critical operating conditions (e.g., higher wind speed, corrosive action of sea salt, etc.). Downtime in offshore installations, given logistical difficulties, is generally higher than that in onshore installations.

In general, technical-scientific literature provides numerous works on WT diagnostic systems [63,64] but provides few details about the different type of faults and anomalies that can occur in WTs, except for the already mentioned work on the statistics [62]. Moreover, there are several datasets containing the real and simulated data related to the WTs and are listed in Table 3.

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Table 3. Anomalies/faults 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]

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Wind turbine PMSG - Short-Circuit Fault	Simulations	Simulation of a mathematical model at $1kHz$ 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], [75], [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 Electrolysers

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].

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

The electrolyser is the device in which the process is host, the main part of which is the electrolytic cell, in which the electro-chemical reaction takes place. A typical electrolytic cell representation is reported in Figure 3. From an overall point of view, the cell is composed by two bipolar plates (anodic and cathodic), 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, that separates the anodic zone from cathodic zone, allowing the selective cross-over of a specific ion through it. Moreover, the Gas Distribution Layer (GDL) aims to allow an uniform access to the gas from the anodic or cathodic plates towards the membrane. The GDLs terminate with a catalytic layer, devoted to promote the chemical reactions hosted at anodic or chatodic sides. The nature of the catalyst depends on the typology of reaction to be promoted: for example, in a Polymeric Electrolyte

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Membrane (PEM) electrolyzer, at the anodic side, catalysts based on ruthenium and iridium are widely used [81] to promote the water splitting in H^+ protons and OH^- anions, while at cathodic side platinum nanoparticles (dispersed on carbon supports) are mainly employed to promote the protons reduction to hydrogen [82].

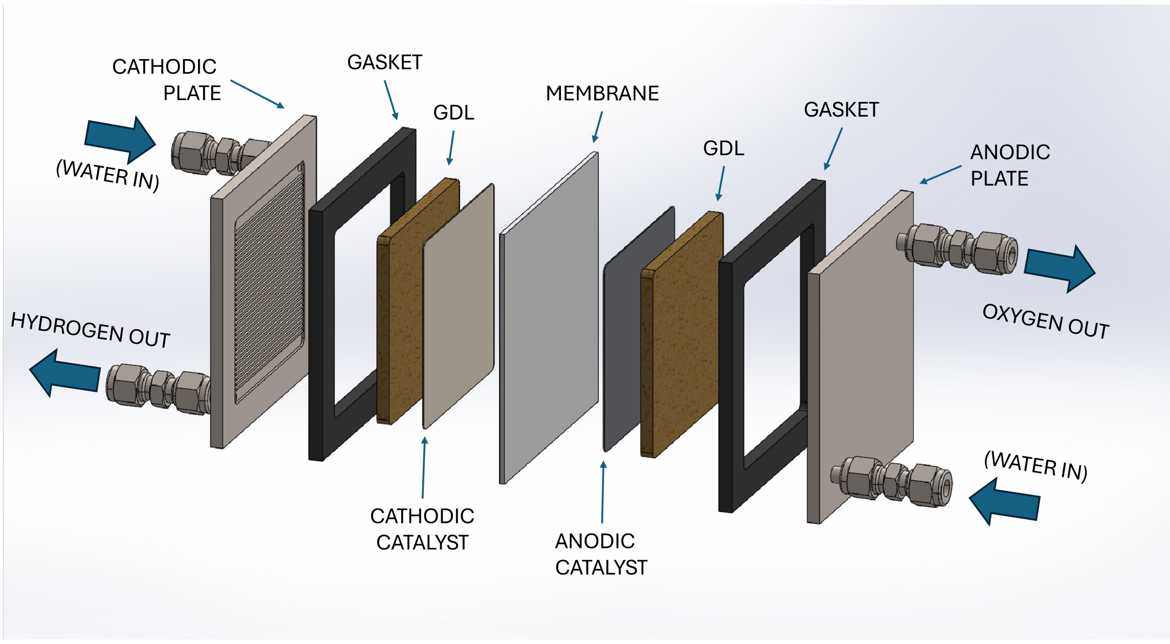

Figure 3. Sketch of a PEM electrolyzer.

2.4.1. 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. Membranes failures are typically associated to 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 temperature effect is more severe with respect to the operative current density [88]. Catalyst degradation is a very slow process, thus is not responsible for sudden cell failure. Among typical catalyst deactivation mechanisms, most common are particles 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 mechanism 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 are 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

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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 electrolysers.

Target component	Description	Cause	References
Membrane	Mechanical degradation	Current collector hole; Widening and narrowing; Non-uniform hydratation; 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 nd 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	

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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 on possible empirical dataset pertaining to electrolyser 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 electrolysers.

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.

$$H_2 + \frac{1}{2}O_2 \leftrightarrow H_2O + Electricity + Heat \tag{2}$$

Of course, depending on the employed FC typology, methane, ethanol, carbon monoxide or other hydrocarbons can be used as fuels, and carbon dioxide can be used as oxidant. In 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 flux in an electrical circuit, thus generating electrical power. FC elements are reported in Figure 4. Main components of the cell are the same already described for the electrolyzer: fuel is fed to the cathodic plate, while oxidant is fed to anodic plate: bipolar plates also act as electrical collector. Reagents are delivered to the catalytic layers through dedicated gas distribution layer; on the catalytic surface, the chemical reactions take place, which mechanism strictly depends on the cell typology. The membrane separating anodic and cathodic sides act as a selective barrier, aiming the cross-over of only a selected ion depending on the hosted process: in the case of PEM-FC, membrane only allow the proton (H^+) crossing.

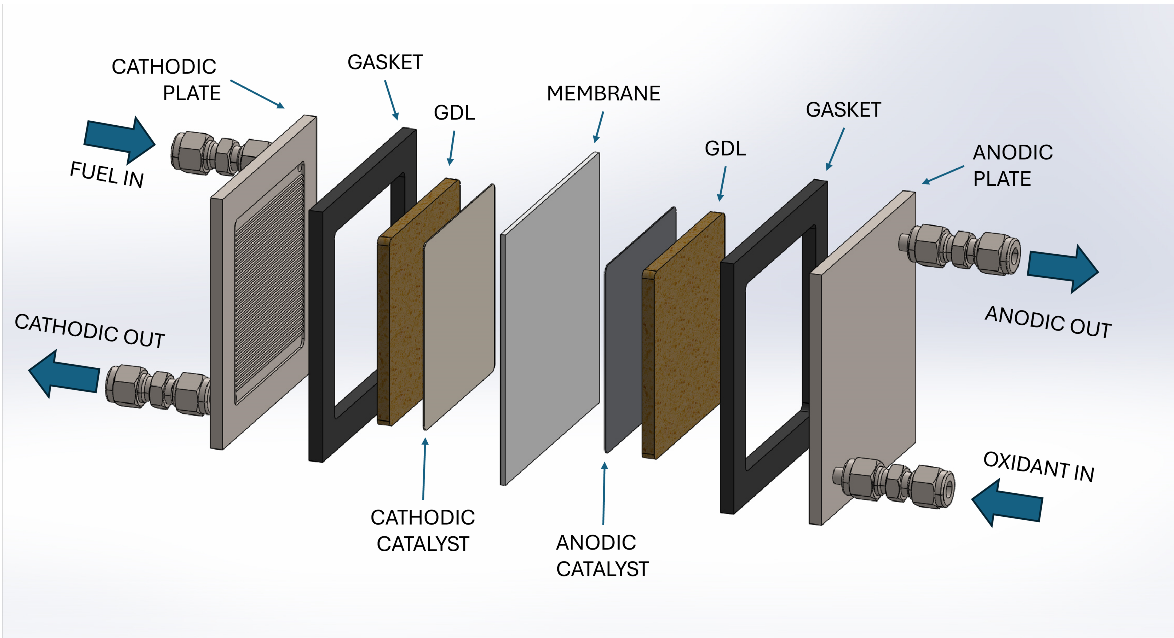

Figure 4. Sketch of a PEM-FC.

2.5.1. 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 for cracking or perforation due to uncontrolled humidity or temperature in the process, that originates to tensile, mechanical and thermal stresses responsible for the failure of the component [96,97], causing the reactants crossover and in turn the uncontrolled fuel combustion [98]. It is worth to underline 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 to a weakening that leads to the membrane failure [100,101]. The second reason for FC failure is catalyst degradation: it could occur for particle sintering [102], carbon monoxide poisoning [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

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plates [101] causing conductivity loss and structure deformation or fracture. GDL can also suffer for embrittlement of the support material due to severe operating conditions as well as to the contact with hydrogen. Finally, non-adequate operating conditions, in terms of temperature or pressure, as well as factory defects, can be responsible for sealing failure originates by 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], [106], [107]
	Thermal degardation	Thermal stresses and cycles	
	Chemical and electrochemical degradation	Contamination; Radical attacks	
Electrodes	Activation loss	Catalyst sintering and unsoldering	[102], [105], [107], [108], [109]
	Conductivity loss	Catalytic support corrosion	
	Reactants mass transport efficiency loss	Mechanical stresses	
	Reduction in tolerance to reactants	Contamination	
	Reduction in tolerance to reactants	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	

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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, not easy to achieve [113]. Several techniques for on-line 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. Anomalies/faults 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-empiric 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 su of all polarization losses	[117]
Catalyst degradation	Predictive mathematical model of catalyst dissolution	The model is based on catalyst transformation theory	[118]

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	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

The survey focused on the currently most widespread BSs technology [121] that is Lithium-ion (Li-ion) technology. The Figure 5 shows a sketch of a Li-Ion battery cell. It has four main components: positive electrode, negative electrode, electrolyte and separator. The separator aims to isolate the electrodes to avoid internal short circuit. Moreover, it is made up of porous material to allow, with the electrolyte, the ions movement between the electrodes.

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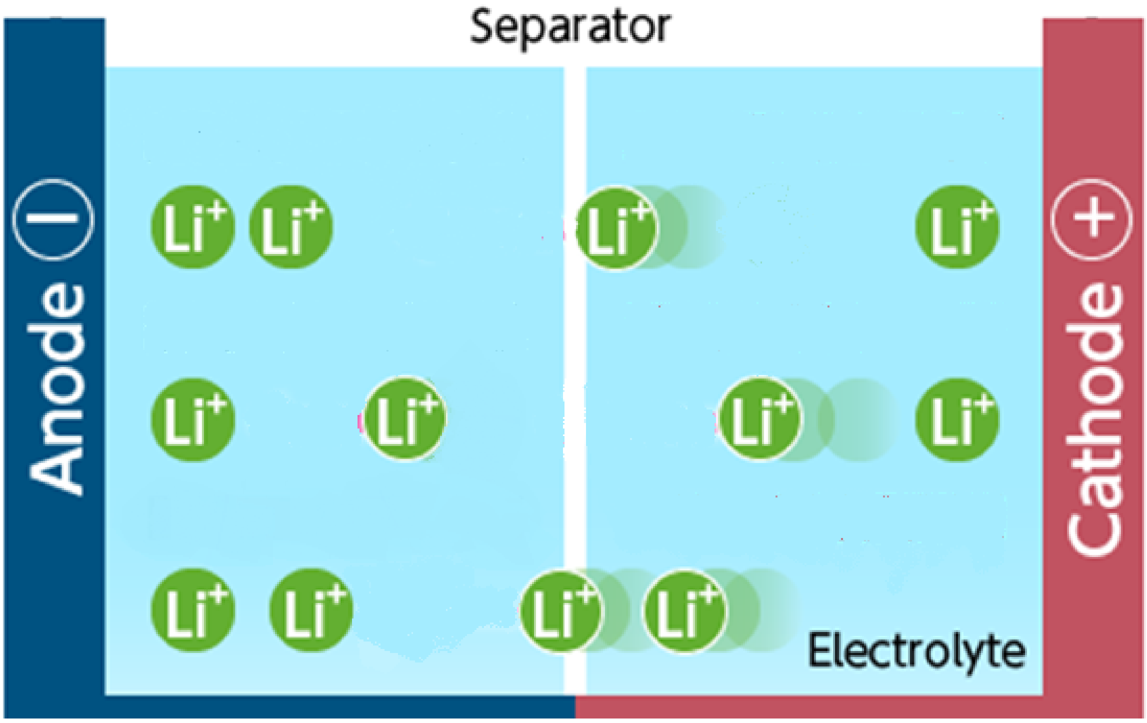

Figure 5. Sketch of a Li-ion battery cell (adapted from [122]).

2.6.1. 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 fault and system fault. The cell faults are mainly caused by Battery degradation phenomena and include the following anomalies/faults: 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 decomposition products of electrolytes. The SEI allows Li^+ transport and blocks electrons in order to prevent further electrolyte decomposition and ensure continued electrochemical reactions [124]; current collector corrosion; internal short circuit (can cause explosion and is mainly caused by overload); thermal runaway; capacity diving; liquid leakage. The system faults are mainly caused by battery management system anomaly/fault [125,126], sensory system anomaly/fault, cables and connections anomaly/fault. 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.

Table 8. Anomalies/faults for BSs.

Target component	Description	Cause	References
	Loss of active material		[127]
	Electrolyte consumption		[128]
	Increase in internal resistance		[129]
	Lithium deposition		[130]
	Gas generation		[123]
Cell	SEI thickening	Battery degradation	[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]

The table 9 highlights the main dataset on faults in Li-ion BSs.

Table 9. Anomalies/faults 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]	

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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]
Cycle Life 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]

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BEEPt	Lab testing	Set of tools designed to support Battery Evaluation and Early Prediction of cycle life 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]	

2.7. Anomalies and Faults in DC/x Conversion Systems

A power electronics converter is a circuit adequately interfacing a power source with an electricity absorbing system, such as a load, a storage or a sinking busbar of the main grid. They are constituted by different stages (Figure 6), including an input and an output filter, a switching stage and a magnetic section. The switching section represents the converter core which can be realized by Metal–Oxide–Semiconductor Field-Effect Transistor (MOSFET) or IGBT devices. A gate driver circuit turns on/off the converter switching devices according to Pulse-Width Modulation/Modulated (PWM) technique assuring its functioning mode.

These converters can be employed as interfaces between a DC voltage source to obtain a DC output voltage of different magnitude or as a DC/AC conversion system. They can be designed and realized to assure unidirectional or bidirectional power flows.

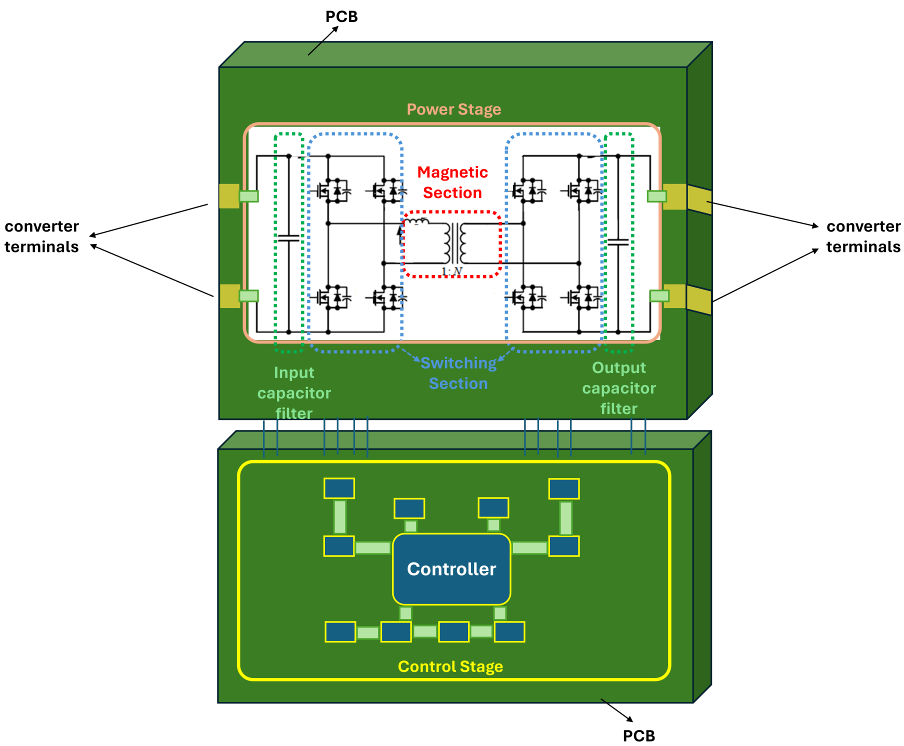

Figure 6. Sketch of a DC/x conversion system.

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2.7.1. Research Highlights

The conducted study highlights the converter is subjected to operating conditions that can vary over time, its devices are subjected to electrical, thermal, mechanical or combined (electro-thermal, etc.) stresses. In addition, aging phenomena can impact the converter performances. These factors can cause anomalies and/or failures to the power stage devices, the control stage, switching components driving circuit, and at the converter inputs and outputs terminals.

The sector literature focused the attention mainly on the physics of the failure and/or anomaly of the individual components, also reporting the converters most damaged/fault devices.

In switching devices, overcurrent and overvoltage conditions can cause the component overtemperature. In particular, the action of thermal stress can have significant effects on secondary breakdown phenomena which lead to the destruction of the switching device. During design phases of such equipment it is essential to consider the safe operating area of these components and appropriate heat sinks. It must be kept in mind that the value of the junction temperature depends on the ambient temperature as reported in (3):

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

where T_j is the switching device junction temperature, T_a is the ambient temperature, P_a is the losses power, and $R_{T_{j-a}}$ is the thermal ambient-junction resistance.

Also the switch Drain-Source resistance, and Gate-Source voltage depend on the junction temperature. The Drain-Source resistance increases to the junction temperature growth (Figure 7(a)) while, in Figure 7(b), the Gate-Source voltage decreases for rising junction temperature values.

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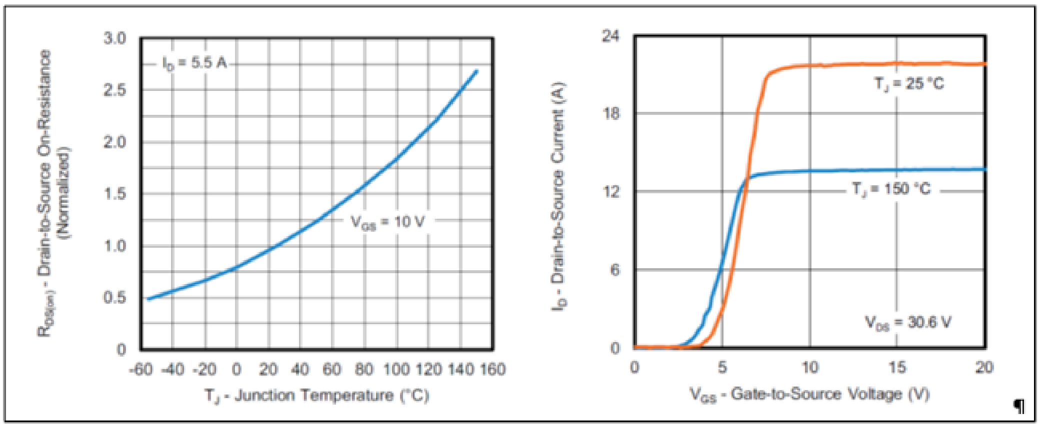

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Figure 7. (a) Drain-Source resistance vs Junction temperature; (b) Drain-Source for different Junction temperature values [149].

The graph reported in Figure 8 underlines that the switch threshold voltage (V_{th}) can decrease to the ambient temperature increase. Given the temperatures that have characterized the latest heat wave phenomena, the threshold voltage V_{th} could drop causing the unwanted switching on of the switching device with harmful consequences for the individual component and also for the interface converter of which it is part.

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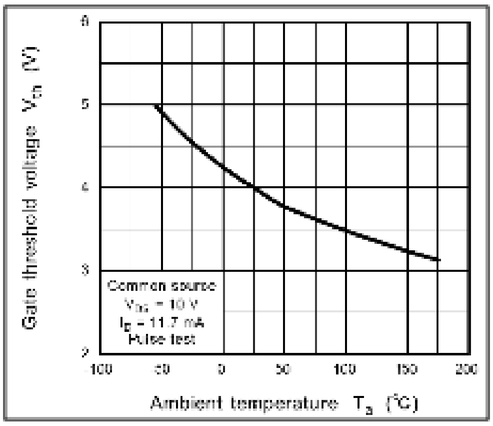
[] 

Figure 8. Typical threshold voltage vs ambient temperature in MOSFETs [150].

Furthermore, it must be underlined that temperature also represents a stressful agent for the materials that make up the switching devices. The use of materials characterized by different behavior in terms of thermal expansion and compression can, in fact, cause cracks with the consequent failure of the component.

A further cause of anomalies and failures in switching devices are electrostatic discharges. In detail, their action can cause the gate oxide to break without obvious malfunctions for the component immediately, but leading to breakage after a period of time from the event. The adoption of protections and the possibility of monitoring the gate charge can avoid the failure.

With reference to capacitive components it is necessary to underline that electrolytic, ceramic and film capacitors are used in interface converters. The capacity of these devices varies with temperature as shown in Figure 9.

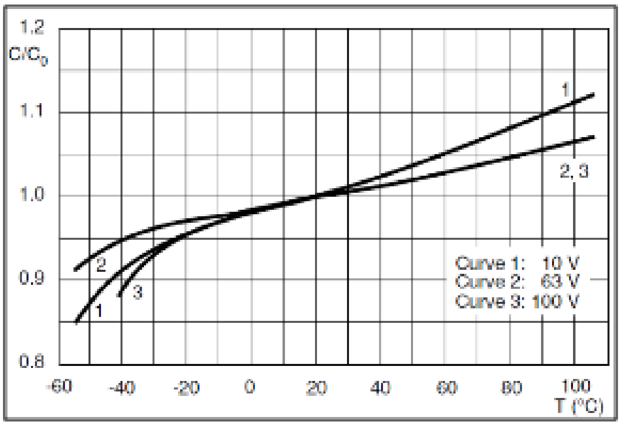
[] 

Figure 9. Typical capacitance (normalized against values at 20°C, 100Hz) vs. temperature characteristics in electrolytic capacitors [151].

The graphs represented in Figure 10 also highlight the halving of the operational life (expressed in hours) of a condenser for every 10°C increase in temperature.

The converter output voltage is obtained by appropriately driving the switching on and off of the switching devices present in the circuit. This function is carried out by appropriate integrated circuits (drivers). They may exhibit anomalous behavior when negative voltages are applied to their inputs or outputs.

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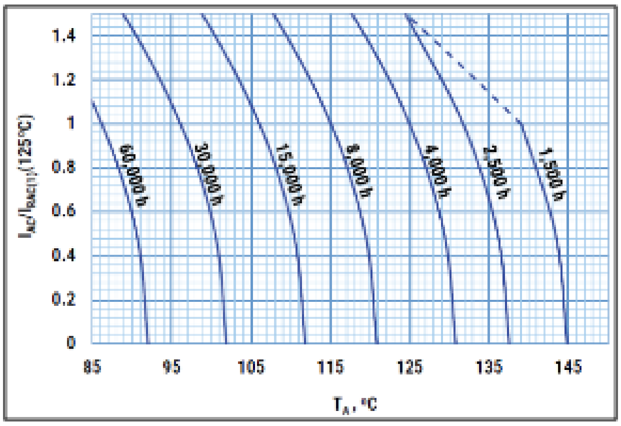
[] 

Figure 10. Typical ripple current (normalized against the maximum value) and operative life vs. temperature characteristics in electrolytic capacitors [152].

In particular, the switching on and off phases (Figure 11) of MOSFETs and IGBTs are characterized by voltage and current transients which, in the presence of parasitic components (capacitances and inductances), can cause the presence of negative voltages at the driver terminals.

The analysis of anomalies and faults occurring in power converters has made it possible to identify the most delicate devices in the power and circuit control stage and the main causes of damages and malfunctions. They are schematically synthesized in Table 10.

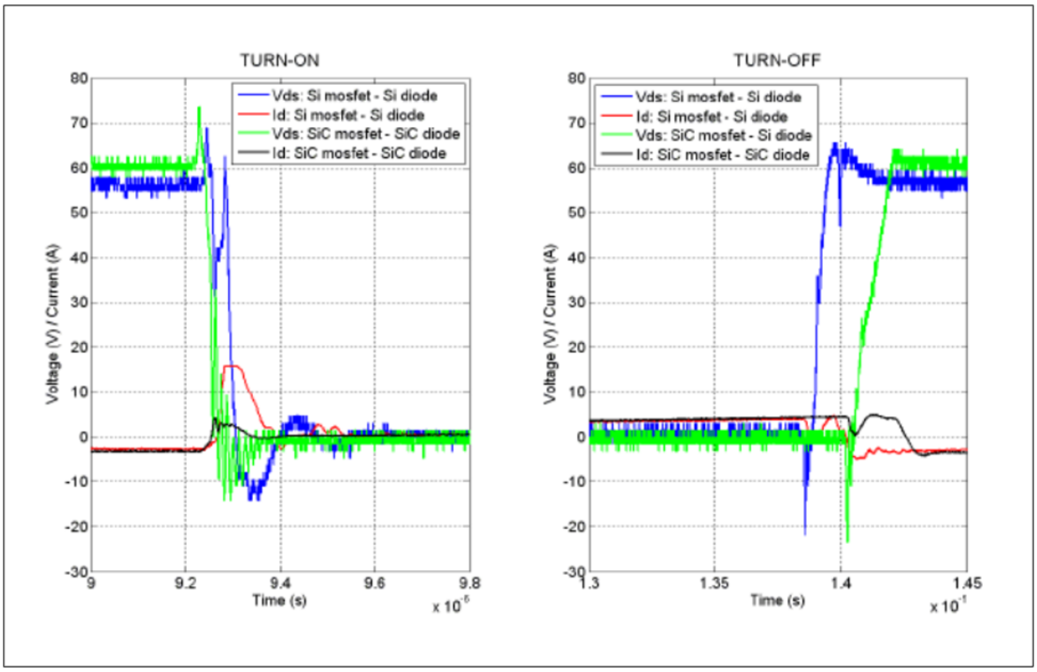
[] 

Figure 11. Typical MOSFETs/IGBTs turn on (left) and turn off (right) characteristics [153].

It is appropriate, in any case, to highlight that it was not possible to find datasets relating to the anomalies and failures of either the interface converters or the switching, capacitive and inductive devices of the power stage, nor of the components of the control stage.

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

Target component	Description	Cause	References
Magnetic/ capacitive/ switching devices	Switches damage	Thermal stress	[154]

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	Capacitor damage	Electrical stress	[155]
	Inductor damage	Thermal and electrical stress	[156]
Printed circuit board	Delamination Cracks Weld deterioration	Aging	[157]
Converter terminals	Power stage devices overcurrent and overtemperature	Terminals short-circuit	[158]
Converter power stage	Ground fault	Worn, frayed, or damaged insulation due to mechanical, environmental, electrical stressing	[158]

2.8. Anomalies and Faults in Monitoring Systems

A monitoring system can be seen as a set of sensors, wiring and user interface as shown in the following Figure 12.

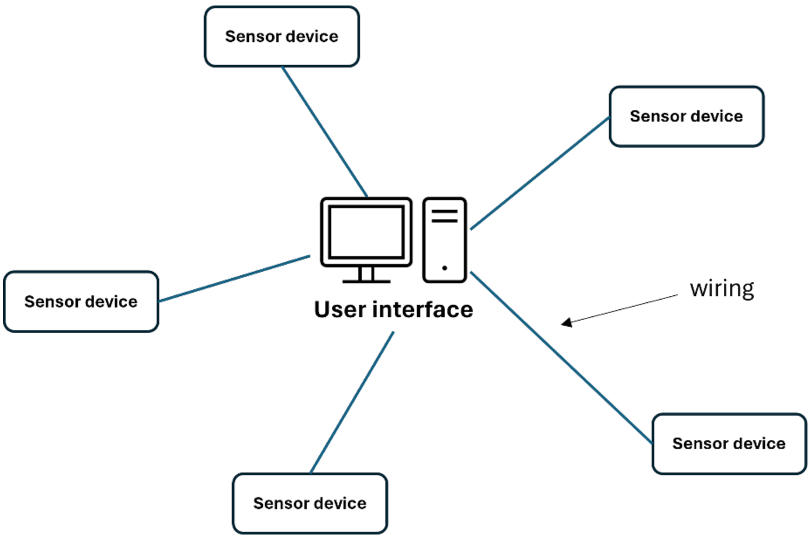

Figure 12. Sketch of a monitoring system.

A software layer is used to manage the data transmitted by the sensors and to give a suitable visualization to the user. The main component that is affected by failures is the sensor so the survey is focused on this.

2.8.1. Research Highlights

The surveyed literature is organized in Table 7. It is highlighted that the main anomalies and faults associated with monitoring system can be listed [159] as mechanical faults regarding to the mechanical structure of the apparatus (e.g. degradation of materials [160], vibrations, external shocks [161]), electrical faults that affect the electrical properties of the device (e.g. loss of insulation [162,163], anomalous measurement residual [164] due to blackout or overloading of the device) and other faults, that can affect the measurement due for example to noise [165], reading errors (value read by the

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device different from the actual one due to a change in gain) [166], calibration losses or performance degradation [167].

The study highlighted that the failures of monitoring equipment strongly depend on the operating conditions of the environment in which they are inserted. The most common are reading errors due to incorrect sensor calibration, performance degradation, or electrical faults; mechanical failures are less frequent.

For all type of faults, it was not possible to find simulated and/or experimental data or information regarding faults and anomalies relating to measurement systems for 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	[160]
		Vibrations and/or external shocks	[161]
	Electrical fault	Loss of electrical insulation	[162], [163]
		Anomalous measurement residual	[164]
	Wrong data	Noise	[165]
		Gain changing	[166]
		Loss of calibration	[167]

2.9. Anomalies and Faults in Communication Systems

The main aim of a communication system is to send and receive data. This system consists of a sender, a receiver and a communication support in order to obtain the data transmission between them. The following Figure 13 shows the principle scheme of a communication system.

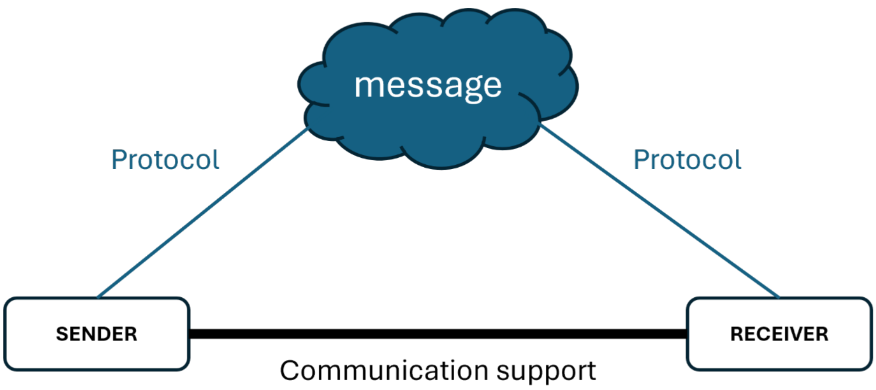

Figure 13. Sketch of a communication system.

The data are packaged in a message by means of a suitable protocol. Therefore, the causes of failure are attributable to multiple subsystems as described in the following paragraph.

2.9.1. Research Highlights

The surveyed literature is organized in Table 12. The study has highlighted that the main anomalies and faults associated with communication systems can be classified [168] into failures of the communication support regarding to the support and transmission medium (e.g. fiber breakage, excessive bending, connectors or splice breakage [169,170]), receiver failure involving a malfunction of the receiver, such as a high data packet reception time [171,172] and data integrity that affect 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 [173]. These last are, generally, recognized

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by the receiver using checksum [174]. The survey has highlighted that failures due to the support medium are more frequent than the other two types.

For all type 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	[169], [170], [173]
Receiver	Receiver faults	Malfunction of the receiver, long data packet reception time	[171], [172], [174]

3. Conclusions

This paper presents a survey on anomalies and faults in renewable-based power systems and may impact their reliability, by addressing several heterogeneous technologies that are therein deployed. Tables related to the literature findings and possible datasets are also reported for reference. In both cases, the survey shows that some aspects are covered by very old articles/references and it is not possible to find up-to-date material. This is a gap that should be filled maybe orienting the study to the specific scope this paper addresses. Furthermore, the survey also highlights a lack of datasets for some technologies, namely electrolyzers, FCs, DC/x conversion systems, monitoring and communication systems. In the case of electrolyzers and FCs, suitable tables report mathematical models that can reproduce the target anomaly/fault phoenomenon and can output synthetic data for further analysis/investigation. And this is another gap that should be filled.

In general, with regards to similar paper, this paper includes many technologies and does not restrict itself to specific ones. For instance, beyond technologies specific to the power domain, also monitoring and communication systems in renewable-based power systems are surveyed. This can help other fellows in orienting their research effort via a self-consistent reference.

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Abbreviations

The following abbreviations are used in this manuscript:

AI Artificial Intelligence

BS Battery System

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EIS Electrochemical Impedance Spectrometry

FC Fuel Cell

GDL Gas Distribution Layer

HAWT Horizontal-Axis Wind Turbine

IGBT Insulated-Gate Bipolar Transistor

Li-ion Lithium-ion

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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