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Review

Advances in Fault Condition Monitoring for Solar Photovoltaic and Wind Turbine Energy Generation: A Review

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Abstract: Renewable energy-based power generation technologies are becoming more and more popular since they represent alternative solutions to the recent economic and environmental problems that modern society is facing. In this sense, the most widely spread applications for renewable energy generation are the solar photovoltaic and wind generation. Once installed, typically outside, the wind generators and photovoltaic panels suffer the environmental effects due to the weather conditions in the geographical location where they are placed. This situation, along with the normal operation of the systems, cause failures in their components, and on some occasions such problems could be difficult to identify and hence to fix. Thus, there are generated energy production stops bringing as consequence economical losses for investors. Therefore, it is important to develop strategies, schemes, and techniques that allow to perform a proper identification of faults in systems that introduce renewable generation, keeping energy production. In this work, an analysis of the most common faults that appear in wind and photovoltaic generation systems is presented. Moreover, the main techniques and strategies developed for the identification of such faults are discussed in order to address the advantages, drawbacks, and trends in the field of detection and classification of specific and combined faults. Due to the role played by wind and photovoltaic generation, this work aims to serve as a guide to properly select a monitoring strategy for a more reliable and efficient power grid. Additionally, this work will propose some prospective with views toward the existing areas of opportunity, e.g., system improvements, lacks in the fault detection, and tendency techniques that could be useful in solving them.

Keywords: fault conditions; fault diagnosis methodologies; photovoltaic systems; renewable energy generation; wind turbines

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1. Introduction

As the energy needs of the modern society have increased, the processes for power generation have been forced to evolve. Thus, the idea of a centralized generation where the sources and the loads are far from each other is less common every day, and new strategies for distributed generation (DG) are preferred instead [1]. The concept of DG is possible, in great measure, thanks to the development and inclusion of renewable generation sources (RGS), such as solar photovoltaic (SPV) and wind power (WP) [2]. The inclusion of RGS supposes some well-known benefits: reduction of pollution and greenhouse gases, utilization of natural and unlimited energy sources, government incentives and subsidies, among others; additionally, it has been reported the existence of some challenges and drawbacks regarding the penetration of RGS being the principal inconvenient the high intermittence in the generation process related with the variability of the sources like sunlight and wind. Unfortunately, the variability of the natural resources is something that cannot be controlled, and the only solution for dealing with it is the use energy storage systems and energy management systems that control how the energy is used. This way, if there is surplus generation, it can be stored and used when the natural resource is unavailable, but the energy is still required. The erratic nature of the weather conditions involves some other issues like power factor reduction, overheating of transformers and feeders associated with harmonic contamination, low power quality in the grid and so on [3–5]. Moreover, and since the power generation with RGS is also a business, before installing any wind farm or SPV plant, it is necessary to perform an analysis of applicable policies, location restrictions, solar/wind resource potential, infrastructure, among others [6]. Finally, it must be mentioned, that any system is prone to present faults either for an incorrect installation procedure or for the normal effects of the operation and wear of the components. In order to avoid financial losses and to guarantee a robust and reliable power supply for final users, it is necessary to determine the state of operation of the whole generation system. This last point plays a major role from both a technical and a scientific point of view. Therefore, a big effort is put in the development of techniques and strategies for the identification of faults in photovoltaic and wind generation systems.

In terms of SPV systems, a large amount of installed capacity was achieved during 2020 with an estimated power of 139 GW installed that year to reach a global estimated 760 GW around the globe [7]. Although this amount seems to be high, it must be mentioned that it represents only around the 1.7% of the global power generation [8]. However, the amount of SPV installed power is expected to continue growing in a great measure because the United Nations implemented the Sustainable Development Goals that, among other things, aim to provide affordable and clean energy highly based in RGS, without compromising the robustness and reliability of the power supply [9,10]. At this point, the techniques and strategies for fault identification become of great importance to ensure this robustness since they can detect an abnormal condition either for preventing or correcting any malfunctioning. In the literature, there are several works that present different classifications for the faults that may occur in a SPV system, with the most studied being the electrical faults, the weather-related faults, and the panel faults [11]. Regarding the electrical faults, they may be associated with problems in the connections or in the electrical components. Typical examples of this classification are line-to-line faults, line-to-ground faults, open circuit faults, arc faults, among others [12–14]. Another group in this classification can be those faults related with the environmental and weather conditions, the partial shading and dust accumulation being the main exponents of this set [15–17]. Finally, the faults that are directly related with the photovoltaic panel are also a common classification. Here, some of the most studied faults are damaged diodes, junction box fault, crack in protective glass, hot spots and connector failures just to mention some [18–20]. What all these faults have in common is that they directly affect the amount of energy that can be produced by the SPV system. In all the cases, a faulty condition leads to a reduction in the generated power, compromising the reliability of the system and, in some cases, producing financial losses for the investors. Since the number of faults related with SPV systems is broad and varies, it is important to count with a considerable number of techniques that allow to identify the different types of faults regardless their nature or behavior.

Regarding to the WP generation systems, according to the Global Wind Energy Council (GWEC) in their annual reports, in the last three years the use of WP generation systems has growth significantly [21]. For instance, in 2019 the new wind power installations added around 60.8 GW to reach an accumulative worldwide wind power capacity of 650 GW. Later, in 2020, the respective new wind power installations added almost 93 GW to reach an accumulative global wind power capacity of about 743 GW, meaning a relative growth of approximately 14% respect to the previous year [22]. Finally, in the last year, 2021, the new wind power installations added almost 94 GW to reach an accumulative global wind power capacity of about 837 GW, meaning a relative growth of 12% respect to previous year [23]. The above quantities and percentages indicate a rising in the use of WP generation technologies, that are wide distributed around the globe [24], which can be noticed by the new onshore and offshore installations [25–27]. The main technologies for WP generation must obey and accomplish the goals established by the 26th United Nations Climate Change Conference of the Parties (COP26) in Glasgow and focused on climate sustainability [28]. To this end, the generation system must be operating in optimal conditions. However, several problems may occur of diverse nature [29]. For example, some problems can be caused by environmental factors [30] like rain [31], humidity [32], dust [33], high speed winds [34], low and high temperatures [35], etc. Additional problems can be caused during installation, e.g., bad design, connection problems [36], geographical restrictions [37], etc. Other problems are referred to the wind power system itself, here, two main branches can be described: electrical and mechanical problems. Thus, from the variety of problems above mentioned that can occur in the WP generation systems, the electrical and mechanical are those on which this review is majorly focused on. Some examples of the electrical faults are, for instance, short-circuit [38], converter faults [39], line to ground fault [40], etc., whereas some examples of mechanical faults include gearbox faults [41], rolling bearing faults [42], and blade faults [43], among others. Therefore, the WP generation systems must be continuously monitored, and several investigations have been performed with the purpose to develop methodologies capable to diagnose the fault conditions present in them [44–49]. In summary, the presence of failures in the WP generation systems depends on the type of technology (onshore or offshore) and the elements that integrate the generation system. A more detailed explanation about frequent faults and proposed solutions in the WP systems will be held further.

This work presents an extended overview of some critical concerns involved in the process of renewable power generation based in the SPV and wind WP technologies that directly impact on their system efficiency, as well as their maintenance costs. Therefore, a detailed framework of the main elements that integrate the renewable power generation systems (SPV or WP) is presented, highlighting those elements that are most frequently studied in the state of the art and their related fault conditions, causes, and consequences. Immediately after, the methodologies, techniques, and schemes that have been proposed for detecting and diagnosing fault conditions in the power generation systems are described. Here, a complete analysis of the base techniques adopted for the development of the proposed approaches and the accuracy in the diagnosis of the fault conditions is carried out. Additionally, a categorization of the methodologies reported is performed, providing the guidelines on what techniques are better under certain system characteristics and for the type of faults analyzed. Finally, an analysis and discussion are presented regarding the trends in the fault diagnosis, new aspects that need to be addressed, proposed methodologies drawbacks, and some promising techniques that could be used for this task. In summary, the review contribution focuses on five main topics: Section 2, (i) frequent fault conditions present in the SPV systems, Section 3, (ii) current methodologies reported in the literature for fault diagnosis of SPV systems, Section 4, (iii) frequent fault conditions present in the WP generation systems, Section 5, (iv) current methodologies reported in the literature for fault diagnosis of WP systems, and finally, Section 6, (v) prospective and tendencies in the emerging methods for monitoring systems and fault diagnosis regarding renewable power generation based on SPV and WTs.

2. Frequent Fault Conditions in SPV Generation Systems

As has been previously mentioned, the use of RGS supposes a series of advantages and benefits and their use has been widely spread in order to attack some environmental and economic issues related with power generation around the world. Among all the RGS the SPV technology presents one of the biggest growth year by year [50]. This situation is mainly explained because of the low cost associated with this type of generation [51], the simplicity of installation and maintenance [52], the all-day availability [53], the high number of National and state-level policies and subsidies [54,55], and so on. Additionally, it has been reported that the use of SPV generation allows to reduce the emission of CO_2 in

2.3 gigatons per year [56]. Thus, SPV generation is becoming an essential part of the new paradigm of the power generation process and, therefore, it is necessary to ensure the proper operation of every element in the system.

It is well known that the operation principle of a SPV generation system is the photoelectric effect, that allows to a semiconductor material to generate and electric current when an electromagnetic radiation hits its surface [57–60]. Depending on how the generated energy is used, a SPV system can work in two different modes: a grid tied mode, and an islanding mode [61]. When a SPV system operates in the grid tied mode, the energy is directly delivered to the main conventional power grid accomplishing the voltage, phase and frequency established by the local standards [62]. On the other hand, the islanding mode implies that the SPV system operates completely independent of the conventional grid [63]. Since it has been mentioned that the power generation process is variable in a SPV system because it depends on the amount of solar radiation that reaches the photovoltaic panel, it is necessary to count with a backup for the moments when the generated power is not enough for satisfying the load requirements. In the case of the grid tied mode, this backup is provided by the conventional grid, whereas in the case of the islanding mode it is necessary to install an energy storage system that may be constituted by batteries or capacitors among other elements [64]. Therefore, the operation mode is an important factor to be considered on the analysis of an RGS, because the components of the system are different for both operation modes. In a grid tied system, the main components are the photovoltaic panels and the power inverter that is the one in charge of converting the DC delivered by photovoltaic panel into the AC with the criteria stablished by the conventional grid. Thus, if a failure exists in the generation system it must be attached to one of these elements or to the connections between them. On the other hand, for an islanding mode of operation, in addition to the panels and the power inverter, a fault condition can appear in the energy storage system or in the regulation system that is in charge of controlling the energy flow. At this point, it is important to mention that from all the SPV installations worldwide, around the 94% are grid tied and only the 6% operate in islanding mode [65]. This situation is explained because the islanded SPV systems have been mainly used for electrifying rural zones where that are not reached by the conventional grid, whereas grid tied systems now are considered another generation plant just like the conventional ones. In this sense, most of the literature focuses on the detection of faults in grid tied connected systems, because they are more widespread and they are also seen as business where a fault may lead to financial losses. Nevertheless and regardless the operation mode of the system, in terms of what can be considered as a fault, all the authors agreed that it can be defined as any condition that results in a loss of the expected output power [12,17]. When the state of fault disappears by itself after a specific period, it is considered as a temporary fault. In contrast, if the failure remains after an extended period it is addressed as a permanent fault [11]. Additionally, a permanent fault can be classified in terms of the severity and the point in the lifetime of the system that occurs; in this sense they can be classified as early faults, extrinsic faults and deterioration [14]. According with the reported literature, Figure 1 shows a classification that shows the main type of faults in SPV systems considering that these faults can be due to environmental factors or a malfunctioning in any component of the installation, but also taking into account the period in the lifecycle of the system where the fault occurs and its severity. In this sense, Figure 1 shows a first level of classification with temporary and permanent faults. In order to understand when a fault is considered temporary and when permanent, five different criteria are selected: duration of the fault, affected components, fault severity, affect on the output power, and possible causes of the fault. Regarding the duration, a fault is considered to be temporary if it lasts from a few to minutes to a couple of days. Furthermore, these faults are self-corrected or they require of almost none human action to be corrected [16]. Notwithstanding, and to be fair, it must be said that dust accumulation is a temporary fault that can lead to a high-severity fault in the SPV panel if left unattended [66]. A permanent fault remains in the system and it cannot be repaired by itself; it necessarily requires of the action of an expert and sometimes it cannot be repaired at all [11]. In terms of the affected components, the temporary fault affects the electric generator, i.e., the SPV panel and its components, e.g., bypass diodes, or it can also affect the power inverter if a maximum power point tracking is not implemented because, in this case, the amount of delivered power could be improved despite de the presence of unfavorable weather conditions. On its part, a permanent fault can also affect the SPV panel and the power inverter, but it can also damage the cables, the supporting structures, the grounding system and even the protections [17]. Speaking of fault severity, the temporary conditions can intrinsically be classified as low severity faults, whereas the permanent faults go from a medium to high since they are conditions that cannot be removed for the system at sometimes [18]. Additionally, it must be mentioned that a temporary fault never causes a complete outage of the production. Rather, it only can reduce the amount of power delivered by the SPV system. On the other hand, when a permanent fault presents a high severity, it can produce a complete interruption of the generated power [14]. Finally, the temporary faults are primarily caused by environmental factors and the permanent faults are caused by deterioration of the components, incorrect selection of the cables and components, improper connections, and overvoltage or overcurrent coming from outside of the SPV system [11]. Continuing with the fault classification, in the case of temporary faults, they are due to cloud presence, partial shadowing, and dust accumulation. On the other hand, the permanent faults can be early faults, extrinsic faults or deterioration depending on when within the lifecycle of the system they occur, and they can be electrical faults or panel related faults. Additionally, Table 1 summarizes the most common faults of every category and provides a brief description of the fault. Table 1 also shows the different types of faults, temporary and permanent, and it mentions every one of the faults that belong to each of the categories describing the main characteristics of the fault and providing some examples of how they are appreciated in an SPV system.

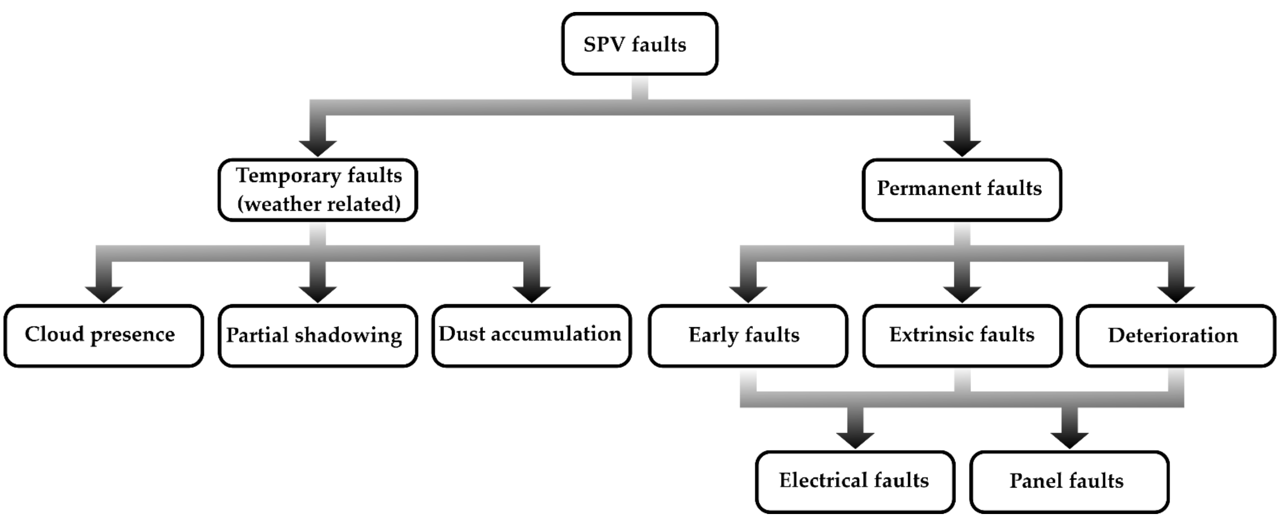


Figure 1. Type of faults in SPV systems.

Table 1. Common faults in SPV system and their description.

Temporary Faults (Weather Related)			
Ref.	**Fault**	**Description**	**Common Examples**
[67–69]	Cloud presence	This condition is presented when a cloud or a set of cloud passes over the photovoltaic panels.	• Temporary loss of power
[70,71]	Partial shadowing	The amount of light that reaches the photovoltaic panel surface is not uniform because	• Temporary loss of power • Temporary hot spots

<table>
<tr><td></td><td></td><td></td><td>some external elements like threes or buildings block the pass of the sun light generating shadows in some parts of the panel.</td><td></td></tr>
<tr><td>[66,72,73]</td><td colspan="2">Dust accumulation</td><td>The dust suspended in the environment is dragged by the wind and it is accumulated on the surface of the photovoltaic panel blocking the light to reach the photovoltaic cells.</td><td>• Temporary loss of power
• Temporary hot spots
• Corrosion of the photovoltaic panel</td></tr>
<tr><th colspan="5">Permanent Faults</th></tr>
<tr><th>Ref.</th><th colspan="2">Fault</th><th>Description</th><th>Common examples</th></tr>
<tr><td rowspan="2">[74–77]</td><td rowspan="2">Early fault</td><td>Electrical</td><td>These are faults that appear early in the lifecycle of the elements of the SPV system that affect the wires and connections between devices or the elements in charge of the energy conversion process like the power inverter.</td><td>• Inverter faults
• Line to line fault
• Ground faults</td></tr>
<tr><td>Panel</td><td>These are faults that appear early in the lifecycle of the photovoltaic panels. These faults are located only in the photovoltaic generator and its components so the DC generation process results affected.</td><td>• Junction box fault
• Bypass diode fault
• Cracked surface</td></tr>
<tr><td rowspan="2">[78,79]</td><td rowspan="2">Extrinsic fault</td><td>Electrical</td><td>The extrinsic faults are considered the midterm problems of the system. As in the case of early faults, an electrical fault is mainly related with problems in the wiring and connections of the system.</td><td>• Line to line fault
• Ground faults</td></tr>
<tr><td>Panel</td><td>In this case this term refers to faults that directly affect the photovoltaic panel or any of its components but considering that the fault occurs at the middle age of the panel.</td><td>• Broken surface
• Bypass diode fault
• Hot spots</td></tr>
<tr><td rowspan="2">[80,81]</td><td rowspan="2">Deterioration</td><td>Electrical</td><td>It is intended that every element in the SPV system will decrease its efficiency and capacities as an effect of the work they perform and aging. When this situation affects the wiring and connections in the SPV system it occurs an electrical fault bay deterioration.</td><td>• Inverter faults
• Line to line fault
• Ground faults</td></tr>
<tr><td>Panel</td><td>The semiconductor material that composes the photovoltaic cells as well as the outer materials that cover them tend to suffer a degradation over the time. The materials that are mainly affected are the silicon cell, the tempered glass cover, the aluminum frame and the panel seals.</td><td>• Corrosion
• Discoloration
• Delamination
• Damaged seals</td></tr>
</table>

Regarding Table 1, it is important to make some clarifications. For instance, all the weather-related faults are considered temporary, because either a cloud or a partial shading is a condition that appears only at a specific time during the day and then disappear. In the case of dust accumulation, this is a situation that can be avoided or corrected by regularly cleaning the panels. Therefore, if one of these situations becomes persistent, it can unchain undesired effects that will result in different permanent damages. In this sense the dust accumulation is the condition that requires the most care, because contrary to the general thought, photovoltaic panels are not self-cleaning. Indeed, it is necessary to schedule maintenance tasks that include the cleaning of the panel surface [72,82]. Otherwise, the efficiency of the photovoltaic panel dramatically decreases and its operation temperature increases causing hot spots and damage of the internal connections. Another important thing to be mentioned is that most of the early faults are related with fabrication defects of any component, a deficient transporting method or an improper installation [83]. Therefore, the faults that can occur at an early stage in the lifecycle of the system are practically the same that can appear later due to deterioration. Finally, it is important to say that the deterioration is a condition that starts at the right moment when the system starts working [81]. However, the effects are negligible at the beginning as they gradually grow to become unacceptable at the end of the lifecycle of the SPV system. All of the aforementioned faults have distinctive characteristics that allow to identify their existence. Thus, several strategies and methodologies have been implemented to properly identify them in order to take actions to prevent catastrophic damages not only to the equipment, but to the health and life of the people in the surroundings of the SPV system. In the next section, an analysis of the different techniques applied for fault monitoring in SPV systems is presented.

Finally, and to summarize the mains aspects of the operation conditions of SPV systems, some key points are listed below [7]:

- A total capacity of 942 GW of energy is produced with photovoltaic systems around the world.
- The biggest producer of SPV energy is China with around the 31% of the global production.
- The production costs regarding SPV systems are reported to be an average of 0.33 US dollar per watt-peak.
- Main maintenance actions are cleaning of the panel surface and revision of the connections and cables.

3. Current Methodologies for Fault Diagnosis in SPV Generation Systems

Every fault condition has different behaviors and characteristics that allow to differentiate one among others. That is why several techniques and methodologies prove suitable for identifying an abnormal condition right at the moment when it appears. A single technique or methodology may be capable of detecting more than one fault condition in a photovoltaic system. Therefore, different strategies are listed and described below for addressing the fault that can be identified by application.

3.1. Techniques for Temporary Fault Identification

It is important to clarify that, in the case of the temporary faults, most of them are inevitable. For instance, it is not possible to avoid the existence of cloudy days. In this sense, most of the methodologies that are being developed for dealing with these types of faults try to forecast the behavior of the sunlight at a specific location or to establish optimal maintenance schedules for preventing long term faults associated with environmental factors. Here, three categories of techniques for the weather-related loss of power will be discussed: the solar forecasting methods, the optimal design methods, and the strategies for dealing with dust accumulation

3.1.1. Solar Forecasting Methods

As the name suggests, the solar forecasting consists of trying to predict the amount of sunlight that will be available at a specific location and at a specific time, and it is one of the oldest efforts for dealing with the variability of the renewable energies like SPV [84]. There are two main typical solutions: those that deliver a mathematical model for the prediction (model-based), and those that only receive a set of data as inputs and deliver an output lacking an equation (data driven). The most common solution for performing a solar forecast is the time series analysis that delivers either a value of the amount of solar radiation or the power delivered by the SPV system at certain hour of the day. Here, the statistical analysis is a very popular solution for finding the relationship between an input and a time series output and for delivering a mathematical model explaining such a relationship. In this sense, the use of simple linear regression models [85] and multiple linear regression [86] provide simple solutions for this problem; notwithstanding that the seasonal autoregressive integrated moving average (SARIMA) has proven to be more effective and reliable [87]. In all these cases, the result is a mathematical expression that predicts the behavior of the output, and it is adaptable to the month and season of the year. Besides the statistical analysis, the use of the artificial intelligence (AI) techniques has shown to deliver good results. Here, different configurations of artificial neural networks (ANN) have been explored. For instance, in [88], a bi-directional long short-term memory (Bi-LSTM) ANN is used for estimating the time series of the solar radiation in a region in the south of China, whereas in [89] the authors propose a convolutional neural network (CNN) for the same purpose. Unlike the statistical regression techniques that deliver a mathematical model, an ANN only delivers a numerical response according to certain input values, but an equation is not obtained. This last representation has become more popular nowadays and techniques such as support vector machines (SVM) represent another option for predicting the solar radiation in terms of different inputs. In this sense, in [90], it is mentioned that the most used inputs for these types of methodologies are climatic variables, e.g., air temperature, relative humidity, wind speed, pressure, among others. Although these methodologies allow the producers and users to be prepared to face the variability of the solar radiation, this is a condition that cannot be avoided, and it is necessary to count with backup systems that allow to save energy and use it when required. This is still an active field where the AI and the machine learning approaches are becoming especially relevant.

3.1.2. Optimal Design and Planification Methods

Many of the faults that appear in an SPV installation are generated by the operation of the system. However, there are conditions that can be avoided if a proper planification is performed before and during the startup of the generation farm. In this sense, the implementation of procedures for risk assessment turns out to be a helpful tool. Since the photovoltaic panels are located outside, there is a high probability of occurrence for lightning events is high. Therefore, the authors in [91] address the importance of implementing a lightning rod system along with a proper grounding mesh for preventing the damages associated to the surges caused by lighting events. In that work, the authors mention that there are two principal schemes for lightning rod systems: attached to the structure and free-standing. The former considers that the structures where the panels are mounted can work as a path for the flow of the lightning current and the last uses a system separated from the mounting structures and directly connected to the ground. Although both solutions are good for prevention, in a lightning rod attached to a structure, the selection of the construction materials and the quality of connections play a major role. On its part, a free-standing installation must consider a correct cable routing to minimize the loop and, therefore, the induced voltages. Due to the importance of the design of lighting and surge protection, in [92], a description and analysis of a method for the proper selection of the components and the procedure for the correct connection of the components are presented. A special attention is put in the best profile for the mounting structures and in the cable selection. These types of works are relevant because the surges that come with lightning events may cause severe damages to the bypass diodes, the power inverters, and to the cable and connection elements of the SPV system.

On the other hand, partial shading is a detrimental condition that generates that the cells that receive low solar radiation turn into loads that consume energy from the non-shaded cells. This situation results in an increment of the cell temperature that causes long-term damage if not attended. Therefore, it is important to detect this condition and take action to diminish its detrimental effects. To overcome the partial shading condition, a first solution consists in performing an optimal design of the system that minimizes the zones that are affected by the shading and that maximizes the generated power. In this regard, the optimization techniques, such as genetic algorithms (GA) [93], particle swarm optimization (PSO) [94] and Markov chain models [95], deliver accurate results. These methodologies consider different configurations of the SPV system by varying parameters like connection among panels and by-pass diodes, orientation of the panels and their location; the optimization technique evaluates the performance of each configuration and deliver as output the system that is less affected by the partial shadow condition. The main disadvantage with this design strategies is that they are passive, and the configuration cannot be changed once installed. Thus, if the surroundings of the SPV systems are modified, then the configuration may not be valid anymore. Therefore, some other authors propose to use active reconfiguration strategies. A reconfiguration consists in changing some of the parameters that define the SPV system, e.g., the connection among the photovoltaic panels, the way by-pass diodes are connected, and the orientation of the photovoltaic panels among others [96]. To perform this reconfiguration, a static or a dynamic approach can be implemented. The static reconfiguration only changes the position of the photovoltaic panels for relocating the shaded cells. With this relocation, the partial shading condition does not disappear, but the affected cells are changed so the output power is maximized and the damage in the cells is reduced. The most explored techniques for performing this task are the puzzle arrangement-based techniques [97] that consider the complete photovoltaic panel as a series of matrices and the algorithm searches the matrix that less affects the performance and orientates the panel so the shadow is directed to this specific matrix. Another option for SPV system reconfiguration is a dynamic approach where some switches are located at specific points in the system allowing to dynamically changing the connection among panels. In this type of approach, the problem to solve consists of selecting the proper location of the switches and determining the best interconnection strategy for minimizing the effects of the partial shading condition [98]. It is intended that if it is possible to install the SPV system in an open space where no object interfere with the pass of the solar radiation it is the best option. However, this is not always possible, and the aforementioned methodologies allow to reduce the risks of premature faults in the photovoltaic system.

3.1.3. Strategies for Dust Accumulation

Dust is a mix of soil lifted, pollutants, and other solid tiny particles that are suspended in the atmosphere and that are carried by the wind. When dust is deposited on the surface of the SPV panel, a layer that blocks the pass of the solar radiation to the photovoltaic cell is formed, generating the same effects as a partial shading condition. To prevent damage associated with dust accumulation, there are two main strategies: techniques for the detection of abnormal levels of dust, and techniques for SPV panel cleaning. Both strategies normally cope with the forecasting techniques previously described, because the prediction allows to know the expected output power and if the measured value presents a high deviation from the expected one it is indicative that there is something wrong in the system. Additionally, both approaches require the measure of certain physical variables as solar radiation and cell temperature. However, the former uses the values of the environmental data only for detecting when the output power is highly reduced by the effect of dust accumulation. In this regard, the use of statistical analysis through multiple linear regression analysis can properly detect when the levels of dust are not tolerable [99]. The main advantage of the statistical analysis is the simplicity of the implementation and the obtaining of a mathematical model that describes the relationships among all the variables. Notwithstanding, these techniques suffer when the relationship among variables is nonlinear. To overcome this situation, again, the AI is a good alternative, and in [100], the use of an ANN is proposed for characterizing, analyzing, and quantifying the level and distribution of the dust accumulation in the surface of a SPV panel. An alternative for identifying dust accumulation that does not require environmental variables consists in using a camera for taking photographs of the SPV panel, and with the use of image processing techniques, such as morphological transformations, it is possible to determine whether the panel is clean or not [101]. Although this methodology delivers accurate results, it is less preferred since the cameras are sensitive equipment that can be easily damaged if they are outdoors.

Regarding the SPV panel cleaning, there have been developed different materials that can be used as coats in SPV panels that allow a self-cleaning process. These are hydrophobic materials that allow to prevent not only dust accumulation, but also the droplet formation related with rain, snow, and ice [102,103]. It has been reported that the use of hydrophobic materials helps to reach an improvement up to 25% in the performance of the system. The main drawback of these coating materials is that they should be integrated since the panel is built, increasing the complexity of fabrication and the production costs. Therefore, the design and implementation of strategies for performing an automatic cleaning of regular SPV panels remain preferred. An interesting solution is the use of electrodynamic devices for dust cleaning [104]. These devices work along with a methodology for determining the level of dust accumulation. When an undesired level of dust is reached, an electric current is directed to the cleaning device generating dielectrophoresis forces that make the dust in the vicinity flow up in the device leaving the panel; i.e., the device acts as sort of a vacuum cleaner for SPV panels. Another option is the use of robotic arms [105] or automatic brush systems [106] that are activated when it is detected that the output power is below a threshold. These machines implement a system that can provide water and soap during the cleaning process resulting in a clean SPV panel. These devices are somehow complex and high cost. Thus, the use of techniques that determine when the dust accumulation is high and perform a manual cleaning of the panels is still preferred.

3.2. Fault Detection Based on Current-Voltage (I-V) Curves

Every SPV panel can be described by two characteristic curves: the current-voltage (I-V) curve, and the power-voltage (P-V) curve. The I-V curve shows the relationship between the current and the voltage delivered by a SPV panel at a specific value of solar radiation, and it considers important values as the short circuit current (I_{sc}) and the open circuit voltage (V_{OC}). On the other hand, the P-V curve shows how the output power of the SPV panel are related. In this last curve it is possible to identify the point where the output power is maximum (P_{max}) and by combining both curves it is possible to find the current and voltage at the point of maximum power (I_{mp} and V_{mp} respectively). All these values are different from one panel to another, and they depend on factors like the peak power of the panel, the construction material, and the surface area among others. These curves can be observed in Figure 2 for a single value of solar radiation. Here, the maximum current that can be delivered by the panel, I_{sc}, and the maximum voltage reached by the panel, V_{OC}, are observed The point where the output power is maximum is known as the maximum power point (MPP) and it always considers values of current and voltage lower than I_{sc} and V_{OC}, respectively. Most of the manufacturers design their SPV panels to operate at an irradiation of $1000W/m^2$. However, it is impossible to keep this level of radiation all the time due to the presence of clouds, the season of the year, and some other environmental factors that may affect the level of radiation that reaches the panel. Therefore, the SPV panel manufacturers usually generate a family of I-V curves considering different levels of solar radiation. In Figure 3a, a family of I-V curves for the SPV panel STKP-60-250 from Solar Electric is presented [107]. By looking at Figure 3a, it can be observed that the lower the irradiation is, the lower the I_{sc} becomes. Although V_{OC} is also affected by the variations in the irradiation, it is not as sensitive to these variations, and it can be considered as almost constant for every level of irradiation. Moreover, the solar radiation is not the only variable that affect the behavior of the I-V curves, the temperature can also severely modify them. Figure 3b presents how the temperature variations alter the performance of the I-V curves. Contrary to what happens in the case of irradiance, temperature variations affect the V_{OC} (lower temperatures generate higher V_{OC} values), whereas the I_{SC} remains almost constant regardless the temperature. Finally, it is expected that if the voltage and current performances are modified, then the MPP is modified too. Hence, as in the case of the I-V curves, there exists a family of P-V curves for any SPV panel. It is important to mention that the highest variations of the MPP are generated by irradiance variations. Thus, the family of P-V curves is generated only considering different levels of irradiation and the temperature variations are left aside. Figure 4 shows the characteristic P-V curves for the STKP-60-250 panel, and it is observed that a reduction of the solar radiation results in a decay of the maximum power. This is a more or less expected situation since it was previously mentioned that when the radiation that reaches the panel is reduced, the I_{SC} gets lower and the V_{OC} remains constant. Therefore, a reduction of the DC power is expected.

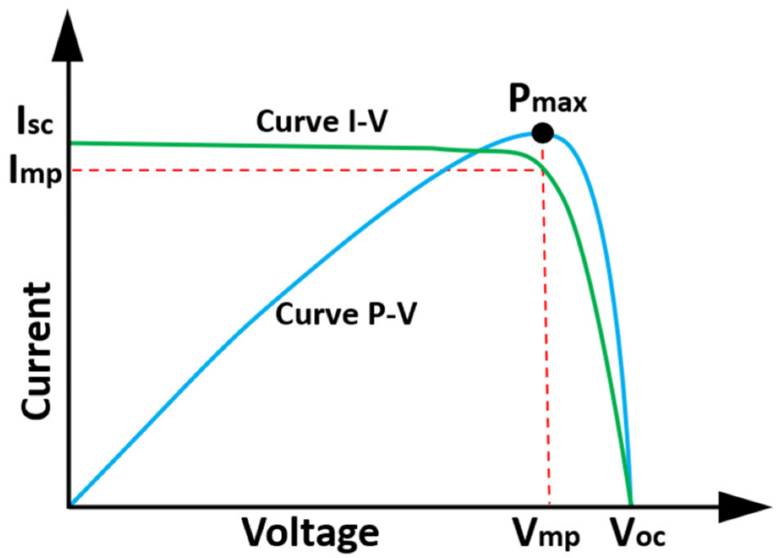
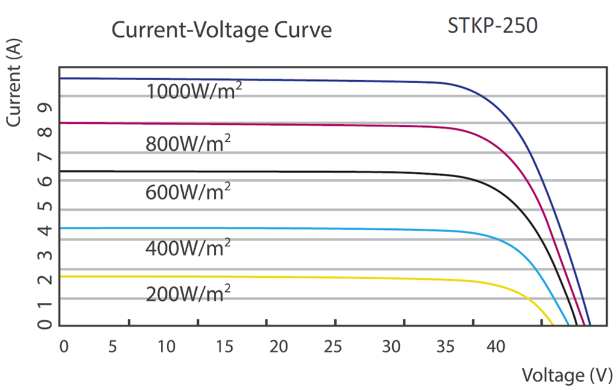
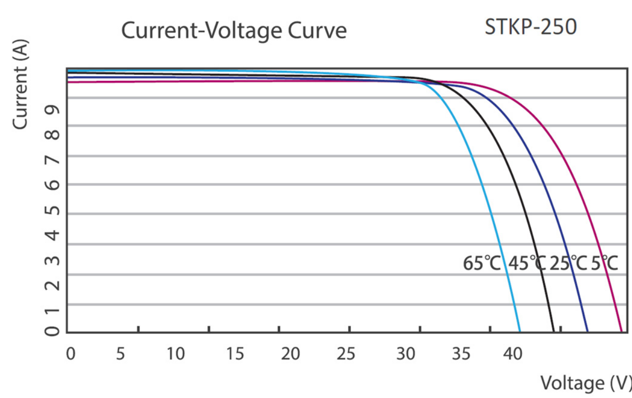


Figure 2. I-V and P-V curves of a SPV panel (adapted with permission from Ref [108] Copyright 2015, Kumar, P., et al.).



(**a**)



(**b**)

Figure 3. I-V curves of an SPV panel for (**a**) different solar radiation conditions and (**b**) different temperature conditions (adapted with permission from Ref. [107] Copyright 2022, Solar Electric London UK).

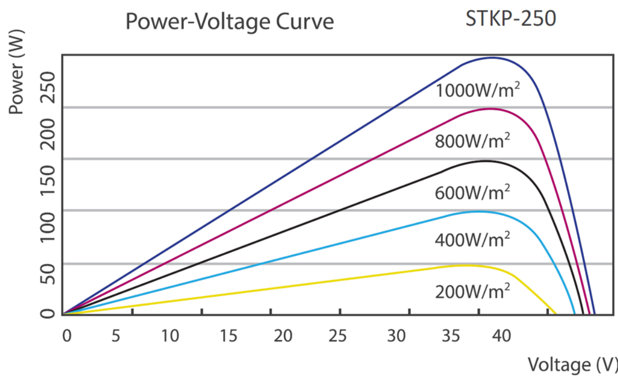


Figure 4. P-V curves of an SPV panel for different solar radiation conditions (adapted with permission from Ref. [107] Copyright 2022, Solar Electric London UK).

The curves in Figures 3 and 4 are extremely important in SPV systems because, as previously mentioned, they define the expected behavior of the SPV panel at a specific solar radiation. Therefore, any deviation from the values on these curves represents an unexpected situation. There are some works that assume this characteristic and use it to perform a fault identification in SPV systems. This technique is suitable for finding any fault that is characterized by a fluctuation in the voltage or current levels delivered by the SPV panel. For instance, in [108], a low-cost system that can compute the characteristic I-V curve of a SPV panel by periodically measuring its I_{sc} and V_{OC} with the aim of identifying abnormal conditions is presented. Moreover, in [109], the authors propose the use of the I-V characteristics of the panel long with a probabilistic strategy based on feature extraction and learning algorithms for the identification of line-line faults in PV systems. Since the I-V curves are different depending on the amount of solar radiation that reaches the PV panel, in [110], the variables of temperature and solar radiation are considered to work along with the I-V curve with the purpose of identifying short circuit, open circuit, and degradation faults in the SPV system. By this data fusion, it is possible to enhance the obtained results and to perform a better identification of more than one fault condition. Finally, a methodology for the detection of line-line faults, open circuit, and bypass diode fault is developed in [111] using the I-V curves and the k-nearest neighbors (kNN) technique for the detection and classification of the different faults. The use of I-V curves is a powerful technique because it directly considers the operation principle of the SPV panels. However, to obtain the best results from this approach, it is necessary to combine the I-V curve analysis with other techniques, such as statistical analysis or AI methods. This is why its use is becoming less popular because these last techniques can be also used by themselves, as shown next.

3.3. Statistical Analysis for Fault Detection

Statistical analysis is a very versatile technique that is applied not only in the identification of faults in SPV systems, but also in many other branches of the science and engineering. With statistics, it is possible to extract trends in the behavior of different physical variables and any deviation in the normal trend is addressed as an abnormal condition. Among all the techniques that are applied in the field of statistics, the analysis of variance (ANOVA) has proven to be effective for the detection of faults in SPV systems. In [112], data from the local temperature, irradiance, and output power for different days in an SPV system with different faults are recorded: bypass diode, open circuit, and degradation. In this work, ANOVA is used for determining variations in the data sets that exceed a threshold and they are associated with a fault condition in the system. Commonly, the statistical analysis is combined with other digital signal processing techniques, as is the case of [113] where the discrete wavelet transform (DWT) is used for separating the fault behavior from the regular operation and then with the exponentially weighted moving average (EWMA) the fault is characterized for its identification. This work requires the measurement of the voltage and frequency from the grid, the current and voltage in the DC and the AC sides of the system, the local temperature, and the solar irradiance and it can identify faults in the SPV array, the junction box, wiring, protections, and the inverter. What all the methodologies that use statistical analysis have in common is that they try to find tendencies in the descriptive variables that are related with the response. It is expected that any fault is companied with a particular tendency and there is where the statistical analysis work for differentiate among faults. Some other well explored techniques in this field are the generalized likelihood ratio test (GLRT) [114] and the principal component analysis (PCA) [115].

3.4. Artificial Intelligence Techniques for Fault Detection

AI is a wide branch of the computer science that, among other things, tries to make decisions that commonly require of human intelligence. All the AI techniques are designed to seek and learn specific trends and characteristics that describe a specific condition. Therefore, their use is suitable in the identification and classification of faults in SPV systems. In this sense, the ANN probably represents the most explored technique. There is a wide variety of ANNs in the fault identification field , including the multilayer perceptron [116], the convolutional neural network (CNN) [117], the probabilistic neural network (PNN), etc. [118]. All these ANN require a data set for training, and data must contain information regarding the faults that are going to be identified so the ANN can "learn" to identify any disturbance. Once the network is familiar with the fault condition, it is able to detect it. Another effective technique for the classification of faults is the fuzzy logic. For instance, in [119], a Sugeno type fuzzy logic system is used, not only for identifying the fault in the system, but also the number of damaged modules. Fuzzy logic is a methodology that delivers good results, but the set of rules for solving a problem can become complex, requiring a high computational effort. Finally, it is important to mention that all these techniques consider that the algorithms learn how to identify an abnormal condition. Therefore, they also belong to the machine learning classification. This is a more or less new term for addressing AI applications that predict an outcome without being explicitly programmed to do it.

3.5. Infrarred Termography

Every object with a temperature higher than the absolute zero emits infrared radiation, and the infrared thermography (IRT) cameras are devices capable of capturing the heat dissipation associated with this infrared radiation. Thus, IRT is the perfect technique for the detection of hot spots in SPV panels. In this sense, in [120], a FLIR thermal camera is used for acquiring infrared images from SPV panels. The images are passed through an image enhance and noise removal filter and then the RGB image is converted in a gray scale image. Next a feature extraction is performed by means of obtaining texture features and some statistical features of the histogram. Finally, a support vector machine (SVM) is used to determine whether or not the hot spot existence. The result is a high accuracy machine learning methodology that uses thermal images as inputs. Another variant of this approach is presented in [121]. Whereas in the previous case, thermal images as used as inputs and a pre-processing stage that uses DWT over the images is implemented to perform the feature extraction over the resultant modes. In this work, the fault classification is carried out by a CNN. Again, this is a processing signal strategy that works along with the IRT. Like these examples, there are many cases with similar procedures, varying only the feature extraction and the classification procedures. For instance, in [122], the transform invariant low-rank textures (TILT) method is used for feature extraction and the PCA for fault detection. In this sense, it must be mentioned that the use of machine learning strategies has proven to be an effective solution for the detection of faults in SPV systems when combined with IRT.

3.6. Machine Learning for Fault Detection in SPV Systems

Among all the modern approaches, the use of machine learning algorithms is one of the most promising in the area of condition monitoring in SPV systems. This strategy belongs to the data-driven methodologies and its operation principle is based on three stages: preprocessing, training, and prediction. The aim of the machine learning techniques is to perform a data analysis to predict an unknown outcome based in the information merged in the data set, i.e., considering a set of inputs that contain the characteristics of a specific process it is possible to determine when exists a condition that generates a deviation from the normal operation conditions. This is why the authors in [123] used machine learning for predicting the output power delivered by an SPV system. There, the electric variables of the system (voltage and current) and the environmental variables (temperature and solar radiation) are used as inputs to form the data set to be analyzed. The authors performed a feature extraction of the aforementioned date using the correlation feature selection (CFS) and relief feature selection (ReliefF) techniques. Then, they used a simple regression model, a Gaussian process regression, and an ANN to determine which of these methodologies delivers the best prediction. They concluded that the ANN is the best tool in this particular case. Another use of machine learning techniques is presented in [124], where the characteristic I-V curves of a SPV panel are used as inputs for the detection of line to line and line to ground faults. From these curves, they extract a total of 16 features that describe the functioning of the system and then use the sequential forward search to select only the best features. Next, using a hierarchical classification technique (HCT) based on three different classifiers (SVM, naive Bayes, and logistic regression) to identify the fault that is present in the system. Moreover, it is worth noticing that some of the works mentioned in the previous sections also implement a machine learning scheme. For instance, in [120], the input data are IRT images and a series of filters is used as a preprocessing stage to obtain statistical features from them later. Finally, an SVM is used as classifier to perform the detection of the fault condition. In summary, machine learning plays a major role in the condition monitoring of SPV systems since it provides a robust and reliable tool not only for the detection of faults, but also for the prediction of the output power delivered by a generation system. This is one of the approaches expected to continue growing with the development of more strategies for the condition monitoring of electric systems.

Finally, Table 2 summarizes the main techniques presented in this section, addressing the types of faults that can be detected with each one of them. Here, it is observed that there are different techniques for identifying the same fault, and the same technique can be useful for the detection of more than one fault.

Table 2. Summary of the main techniques for fault detection in SPV systems.

Ref.	Year	Classification	Technique	Fault
		Solar forecasting		
[85]	2020	Model-based	Simple linear regression	• Power loss due to clouds
[86]	2020	Model-based	Multiple linear regression	• Power loss due to clouds
[87]	2020	Model-based	SARIMA	• Power loss due to clouds
[88]	2021	Data-driven	Bi-LSTM	• Power loss due to clouds
[89]	2020	Data-driven	CNN	• Power loss due to clouds
[90]	2021	Data-driven	SVM	• Power loss due to clouds
		Optimal design methods		
[93]	2018	Data-driven	GA	• Partial shading
[94]	2021	Data-driven	PSO	• Partial shading
[95]	2021	Data-driven	Markov chain models	• Partial shading
[97]	2022	Data-driven	Static reconfiguration with puzzle arrangement.	• Partial shading

[98]	2021	Data-driven	Dynamic reconfiguration	• Partial shading
		Strategies for dust accumulation		
[99]	2018	Model-based	Multiple linear regression	• Dust accumulation
[100]	2022	Data-driven	Deep residual neural network	• Dust accumulation
[101]	2020	Data-driven	Image processing and ANN	• Dust accumulation
[102]	2020	Not applicable	Self-cleaning coat	• Dust accumulation
[103]	2022	Not applicable	Self-cleaning coat	• Dust accumulation
[104]	2020	Data-driven	Electrodynamic cleaner	• Dust accumulation
[105]	2019	Data-driven	Robotic arm	• Dust accumulation
[106]	2018	Data-driven	Automatic brush system	• Dust accumulation
		Fault detection based on I-V curves		
[108]	2022	Data-driven	I-V curve	• Power loss
[109]	2020	Data-driven	I-V curve with probabilistic analysis	• Line-line fault • Line-ground fault
[110]	2019	Data-driven	I-V curve with environmental conditions	• Short circuit • Open circuit • Degradation
[111]	2018	Model-based	I-V curve and the kNN technique	• Line-line fault • Open circuit • Bypass diode fault
		Statistical analysis		
[112]	2020	Model-based	ANOVA	• Bypass diode fault • Open circuit • Degradation
[113]	2018	Data-driven	DWT with EWMA	• Faults in the SPV array • Junction box faults • Line-line fault • Line-ground fault • Fault in protections • Inverter faults
[114]	2019	Data-driven	GLRT	• Mismatch • Bypass diode fault
[115]	2021	Data-driven	PCA	• Line-line faults • Line-ground faults
		Artificial intelligence techniques		
[116]	2020	Data-driven	Multilayer perceptron ANN	• Panel disconnection
[117]	2020	Data-driven	CNN	• Open circuit • Line-line fault • Arc fault
[118]	2018	Data-driven	PNN	• Short circuit • Open circuit • Abnormal aging
[119]	2020	Data-driven	ANN and Fuzzy logic	• Open circuit • Short circuit
		Infrared thermography		
[120]	2020	Data-driven	IRT with SVM	• Hot spots
[121]	2021	Data-driven	IRT with CNN	• Hot spots
[122]	2021	Data-driven	IRT with TILT and PCA	• Hot spots
		Machine Learning		
[122]	2019	Data-driven	CFS-ReliefF-ANN	• Output power forecasting

[123]	2021	Data-driven	HCT with SVM, Naive Bayes, and Logistic Regression.	• Line to line • Line to ground

Before continuing, it is important to say that although Table 2 presents a classification of the main techniques used for the fault detection in SPV systems, some the works listed there can fall within more than one of these categories since they are composite methods. For instance, the work in [109] uses the characteristic curves of the SPV panel, but it also uses statistical analysis. On their part, the works [120–122] all consider the use of as well as a machine learning approach. This is a common practice that tries to use the strengths of two or more methodologies and combine them to improve the results. In this sense, it is expected that these types of methodologies continue being implemented for the condition monitoring of SPV systems.

4. Frequent Faults Conditions in WP Generation Systems

In general, wind power is one of the three major renewable energy sources along with solar power and hydropower, and as energy source, wind is well distributed around the globe being suitable to be exploited in human activities for the general society welfare, even having the disadvantages of intermittency and unpredictability [125]. For that reason, the use of the technologies that extract energy from the wind, better known as wind turbines (WTs), is nowadays very important and requires continuous actions for keeping their operation as optimal as possible in order to reach the goals established by the international regulatory dependencies [10,28]. Thereupon, it is well known that current WTs are modern machines that convert the kinetic energy of the wind into mechanical energy and in turn into electrical energy, where different aspects are considered for maximizing the output, minimizing the maintenance costs, and increasing the efficiency and the reliability [126,127]. In this way, the WP systems have been, year to year, increasing their installations capacity because both sectors, public and business, face the necessity to move away from fossil fuels toward alternative and sustainable technologies, for solving the problems of energy security, climate change, and affordability [23,28].

Regarding the wind power generation technologies, a categorization of the WTs can be performed according to [125,128] by considering different aspects, e.g.:

- according to the geographical location for installation
- the turbine power output capacity
- the turbine blade rotor-axis configuration
- the airflow path to the turbine rotor
- the rotor-generator coupling (drivetrain)
- the power supply connection mode

According to the previous points, the WTs are classified based on their geographical location in two main branches: onshore and offshore. In this field, the onshore WTs are those located on land having easiness to access, low costs of maintenance and installation, and easier integration to the electrical grid [129]. By its part, the offshore WTs are those located in coastal waters having, respectively, excellent and continuous wind resource, higher power output generated, more operating time along the year, less environmental restrictions [130]. According to the power output capacity, the WTs are classified like micro (a few kW), small (<100 kW), medium (100 kW–1 MW), large (1 MW–10 MW), and ultra-large (>10 MW). For example, in some zones where the electric network is not available, the use of micro-WTs operating at moderated wind speeds for minor functions, such as street lighting and water pumping, is preferable [131]. The small WTs are typically installed in rural zones for residential houses, farms, and small facilities of some telecommunication companies that require electric energy [132]. The medium WTs consider applications for powering villages, hybrid facilities, power plants, among others, and can be connected on-grid, or off-grid [133]. Meanwhile, the large WTs and ultra-large WTs are used for industrial applications typically with inter-connection to the grid [134].

According to the blade rotor-axis configuration, the WTs are divided in two branches: horizontal-axis and vertical-axis. Most of the WTs installed are horizontal-axis, because the wind flow is parallel to the rotation axis of the blades [135]. By its part, the vertical-axis WTs can acquire the wind flow from any direction [136]. According to the airflow path in relation to the turbine rotor, the horizontal-axis WTs can be divided in two types: upwind and downwind. In the first ones, the rotor face directly the wind, meanwhile, in the second ones, the wind flows first through the nacelle and tower and finally the rotor blades [137]. According to the generator-driving, there exist two types of WTs: direct-drive and geared-drive. In the direct-drive WTs, the blade rotor and the generator are directly connected by a shaft, increasing their efficiency, reliability, and design simplicity [138]. In the case of geared-drive WTs, a multistage gearbox is used for the coupling between the blade rotor and the generator to increase the rotation speed achieving higher power output [139]. Finally, according to the power supply mode, the WTs can be grouped as: on-grid and off-grid. The off-grid WTs are generally those of micro and small size, used for domestic applications in rural zones, residential houses, etc. [140]. The on-grid WTs are commonly those of medium and large size, used for grid connections [141]. In addition to the previous categories, there exists an alternative classification of the horizontal-axis WT (HAWT) and the vertical-axis WT (VAWT) [142,143]. From these, different subcategories can be defined, like those depicted in the Figure 5 in the tree diagram. As observed from Figure 5, the rotor-axis configuration is classified according to two main types of WTs: HAWTs and VAWTs. For HAWTs, a subclassification considers Dutch, multibladed, and propeller types of WTs. In turn for the propeller type WT there exist variations according to the number of rotor-blades as one-blades, two-blades, three-blades, etc. Meanwhile, the VAWTs are divided in Savonius and Darrieus type WTs.

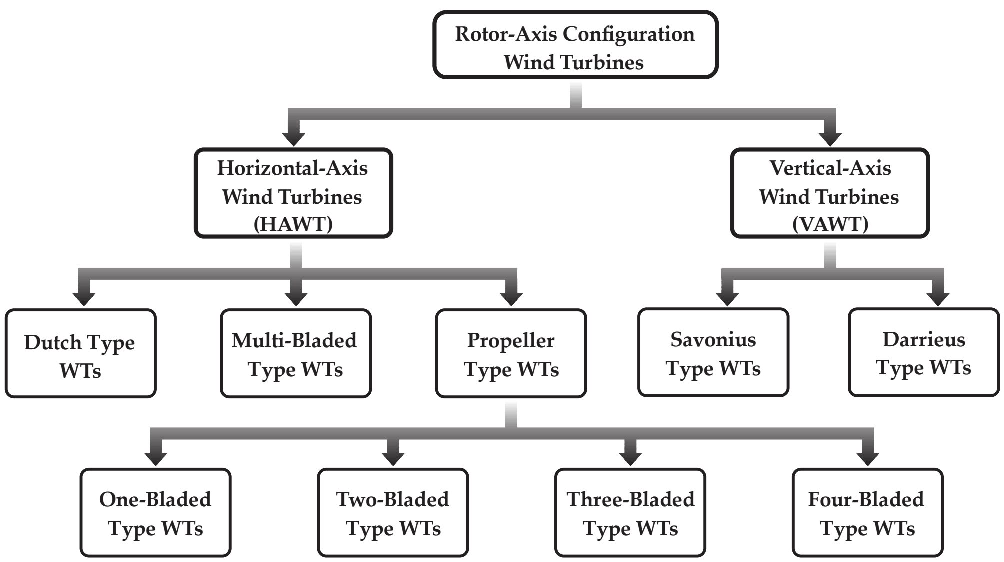


Figure 5. Classification of WTs according to the rotation-axis like HAWTs and VAWTs type (adapted with permission from Ref. [142] Copyright 2021, Bhattacharjee, S).

There exist specific characteristics for each one of the subvariants of Figure 5. However, for the sake of simplicity and considering that in the classifications the common general branches are HAWT and VAWT, they will be adopted and referred to in the future. Although several authors agree that most of the WTs installed around the world are the HAWT types because of the technology mature and their performance, recently these turbines have faced several challenges for the generation of multi mega-watt range, and the VAWT types could be a possible solution [144–146]. Therefore, it is important to identify the main components for these two types of WTs. In one hand, the VAWTs are omni-directional wind catchers devises, a reason for which they have fewer components than

HAWTs and require less maintenance, but their main components also depend on the turbine subtype (Darrieus or Savonius) [145]. In general terms, the components of VAWTs look to achieve, like any other devise, the best efficiency, obeying three basic aspects namely the airfoil, the solidity, and the blade design [146], so the elements can be grouped as [125,142,147]:

- Blades, which could be curved (bend) or straight (flat) [146].
- Rotor shaft ensemble, that considers the rotor shaft, the upper and lower bearings, the brake system (disk and caliper), rubber isolators, torque sensors, and the coupling to the drivetrain [147].
- Tower or foundation, enclosing the drivetrain and control system, gearbox, and generator [147].
- Rotor column or stator shaft, possibly including the upper and lower hubs, and the guy wires [142].

On the other hand, the modern HAWTs vary in terms of design and power ratings, but the majority are the propeller type [128], from the three-blade type (most common) to multiple blades [125]. Several authors, consider as main components the followings [36,39,125,128,142,143,148]:

- The foundation, in general terms, is a base structure for giving support to the WT by connecting the tower to the ground [128].
- Tower: This component is a structure that supports the nacelle, the rotor, and the blades allowing them to reach an adequate height for catching the wind flow [142].
- Blades: Components designed to catch the wind flow for converting kinetic energy of the wind into mechanical energy, that means, movement of the WT rotor [143].
- Nacelle: A structure that encloses and protect the drivetrain of a WT from environmental conditions, i.e., a housing for the coupling of the kinematic chain break-gearbox-generator [125].
- Break: Normally the WTs do not operate at extreme rotational torque or speeds, for these cases a brake system is designed to slow down the turbine at a cut-out wind speed for safeguard it [143].
- Gearbox: A mechanical element that connects the blade rotor to the generator for matching the speed difference between them, by converting the low-speed high-torque from the blade rotor shaft into high-speed low-torque of the generator shaft, to raise the power output of the WT [36].
- Generator: Converts the mechanical power into electrical power thanks to the high rotation speed achieved by the gearbox from the blade rotor, thus the energy is obtained by spinning cooper windings in a magnetic field [39].
- Power converter: Many WTs are equipped with a devise that converts the AC power output to a DC signal for storage purposes [148].

Having identified the general components of HAWTs and VAWTs, following in this study is an analysis of the frequent failures or fault conditions. Prior to this, however, a general classification of those faults will be adopted by considering two groups: Electrical and Mechanical.

A brief summary of the main aspects regarding the operating conditions of WP generation systems is listed below [7]:

- Around 845 GW of energy are generated using WP around the world;
- The biggest producer of this type of energy is China with the 40.5% of the global production;
- The global weighted-average cost of electricity for WP projects has reached the 0.033 US dollars per kWh, making this energy the cheapest;
- Since WTs include many mobile parts, their maintenance is complicated and requires a shutdown of energy production;

- Main maintenance tasks include the lubrication of the moving parts, revision of the blades, the connections, cables, and protection of the whole system.

4.1. Faults in the Electrical Components of WTs

In relation to the most common faults, regarding the electrical components of HAWTs and VAWTs, some sensible components are prone to fail, e.g., the generator, the power converter, and the controller, among others [147,148]. For example, in [30], a collection of environmental conditions, including humidity, temperature, and salt conditions of the geographical location, negatively affects the lifetime of the electrical components of a WT installation, by wearing and corroding elements, e.g., contacts and wirings, and even the materials of the foundation, nacelle, and blades are deteriorated. In addition, the investigations carried out by [32] clearly indicate how the amount of humidity cause a reduction in the kinetic energy of the wind. As a consequence, the amount of power production by a WT is reduced, yielding less production in winter than summer. On another topic, some works address the relation between the wind speed and possible failures in the power converter system since the reliability of a power device depends on factors, such as its topology, the electronics components' reliability, the operating temperature, etc. In this sense, a failure in the semiconductor is directly related with their junction component temperature, so, the wind speed defines the power flow through the converter and so will the components temperature of the junctions [34]. By other part, the WTs that are connected to the grid can be affected by the faults present in the power lines, e.g., tripping of transmission lines, short-circuits, or loss in the production capacity, causing, for instance, malfunctioning in the operation of the generator and the power converter [36]. Moreover, during short circuits in WTs connected to the grid, the current could yield in a voltage drop in the generator terminals that spur an electromagnetic torque reduction that leads to a rotor acceleration and voltage reduction. As a result, as voltage decreases, high current transients are generated in the generator stator and rotor, affecting the power converter [39]. By the other part, some problems are present when the WTs are connected in wind farms and the collector system uses a set-up substation transformer in a delta connection at the collector side, because this system is non-effectively grounded. Therefore, a single-phase-to-ground fault can be developed to a three-phase-to-ground fault. It is worthwhile to mention that these faults are caused by improper fault isolation [40]. Moreover, several studies have revealed that power converter failures are the principal cause for WT stops and shutdowns mainly caused by the presence of short-circuit faults and open-circuit faults in the power switch, making the converter replacement very expensive [148]. Therefore, the failure of power converters is very common, but faults can also be caused by abnormal operations of the grid, the loads, as well as the generator problems [49]. Additionally, when the power converter fails, this can in turn damage the peripheral components of the WT, e.g., the generator and other electrical elements, generating abnormal operation of the whole system [149]. Other examples of faults are the short-circuits than occur in the large power ratings WTs, which are typically in the high temperature superconducting (HTS) generators, characterized by their small reactance making them sensible to higher fault currents and large torques [38]. These HTS generators can be damaged by the presence of short-circuits in the three phases, phase to phase clear of earth, phase to phase earth, and phase earth, caused by large forces from the WT rotor. Finally, when the stator, or the rotor, in generators of offshore WTs present problems due to the high electric and thermal stresses, then asymmetries are introduced into the generator causing faults that are reflected as a temperature rising observed by the supervisory control and data acquisition (SCADA) system of the turbine [150].

4.2. Faults in the Electrical Components of WTs

On the other hand, the faults regarding the mechanical components of HAWTs and VAWTs consider those problems that could be present in the components like the gearbox, the blades, the main bearings of the WTs, among others [41]. For example, the work in [21] presents an overview of the failure modes of the WT bearings for large-scale power generation. This review presents three main aspects: a subdivision of WT bearings like gearbox bearings and adjustment system bearings, failure modes of the bearings, and causes and consequences. Therefore, it is mentioned that typically the main bearings in WTs suffer from changes in their temperature due to load variations and changes in the rotation speed. However, there also exist other factors that affect the normal operation of the bearings connected, for instance, to the gearbox, e.g., unbalance, rolling bearing breakage, or grease excess in the bearings, caused by load variations, changes in rotation speed, or bad maintenance [42]. The rolling bearings of WTs installed in wind farms are subject to adverse conditions variations like the wind speed, for long-term periods, also icing and dust accumulation in the rotor-blades cause load variations in the main shafts of the drivetrain affecting these elements causing elements wear [151]. Besides, WTs gearboxes are one of the principal components that could lead to shutdowns of the entire drivetrain causing major economic losses, some factors like cracking or breakage in the elements, broken tooths, elements wear or aging, corrosion, among others, may cause a problem in the gearbox [152]. In this sense, during WT operation, if the gearbox has faults on its elements, such as journal damage in the gearbox [44] or bearing imbalance [45], then sudden drops in the generated power, voltage, current, and rotation speed are observed in the generator output, even when the wind speed keep into their normal ranges for system operation. In contrast, in the work presented by [48], planetary gearbox faults are studied by using a real WT but simulating the faults. That study considers damages in two principal elements of the planetary gearbox: bearings (inner race, outer race, inner-outer race, balls) and gear (broken tooth and gear wear). Last, but not least, some studies handle with the problems related to the WTs rotor-blades failures. In this field, the work in [31] contains a study of the coating rotor-blades of WTs that get fatigued by the impact of raindrops or rain erosion. This study considers a variety of raindrop characteristics, such as impact speed, impact angle, drop size, and shape (flat, spherical, and spindle). From that work can be concluded that erosion by rain in the coating rotor-blades material may lead to a crack initiation and propagation, which is very harmful for the blade structure integrity. However, not only the rain, but also the effect of the dust in the wind may change the rotor-blade properties. For instance, the work presented in [33] presets an investigation of the effects of dust on the rotor-blade surface, concluding that roughness is altered by the accumulation of dust particles. In this same line, it can be said that other environmental factors, such as temperature, specifically speaking about very low values, affect the rate of erosion mechanisms of the coating of rotor-blades as described in [35]. In such research, it is found that low temperatures affect the wear-related properties of the coating polymer, such as its ductility, and hence, erosion caused by dust, sand, and hailstones is accelerated, damaging mainly the leading-edges coating of the rotor-blades.

In Table 3, the most frequent faults in the WTs (HAWTs and VAWTs) are presented, summarizing the year, reference number, type of fault, a simplified description, and some examples.

Table 3. Summary of the common faults of WTS reported in the literature. Considering electrical and mechanical components faults.

Ref.	Year	Fault	Description	Examples
			Electrical Components Faults	
Ref.	**Year**	**Fault**	**Description**	**Examples**
[30]	1999	Degradation	Wheatear, or environmental conditions, affect the electric materials of the WTs components.	Corrosion in contacts, wires, and generator elements
[36]	2015	Power disturbs	Power disturbs in the on-grid connection damage the generator and power converter of WTs.	Voltage variations, short-circuits, and voltage unbalance.
[39]	2009	Failure of power converter	Torque reduction in WTs cause current transients in the generator affecting the power converter.	Short-circuit in the on-grid connection.
[49]	2021	Failure of power converter	Problems caused by anomalies in the grid, loads and generator problems.	Power disturbs, variations in load, generator problems
[32]	2019	Loss power generation	Humidity changes air density reducing the amount of power production in WTs	Loss of power in the generator output.
[34]	2012	Failure of power converter	Changes in wind speeds vary the power through the converter, causing temperature changes affecting its hardware.	Temperature changes of the power converter hardware.
[38]	2017	Failures of the generator	Large forces cause short-circuits in high-temperature superconducting generators affecting their operation.	Short-circuit in high-temperature superconducting generators.
[40]	2018	Sigle-phase-to-ground fault	Collector systems of WTs are not effectively grounded and substation transformers are delta connected at collector line side.	Sigle-phase-to-ground fault in collector system
[148]	2022	Failure of power converter	Short circuits faults and open-circuits fault cause failures in the power converter of WTs.	Short circuits faults and open-circuits faults in the power converter.
[150]	2021	Failure of the generator	The stator and rotor problems usually occur because of the high electric and thermal stresses introducing asymmetries in the generator of WTs.	Thermal stress in the generator
			Mechanical components faults	
Ref.	**Year**	**Fault**	**Description**	
[21]	2020	Bearings faults	Overview about failure modes of two main branches of bearing in WTs: gearbox bearings and WT adjustment system bearings.	Faults in gearbox bearings and adjustment system bearings
[42]	2020	Bearings faults	Damaged by factors like load variations, fatigue, or bad maintenance.	Imbalance, breakage, and excess of grease in the rolling bearing.
[151]	2021	Bearings faults	Adverse conditions like long-term and variable wind speed, variable load can compromise the integrity of WTs bearings.	Bearing fault: ball fault, inner raceway fault, outer raceway fault.
[152]	2021	Gearbox faults	The gearbox can be damaged by elements cracks, corrosion, aging, wear, etc.	Rotor imbalance and gearbox faults
[44]	2022	Gearbox faults	When gearbox components are damaged drops in voltage, current and power of the generator are observed.	Gearbox bearings failure, or journal damage in the gearbox.
[45]	2022	Gearbox faults	Industrial WTs have imbalance problems in the gearbox caused by damages in the gearbox bearings, gear aging or breakage.	Imbalance in the gearbox bearings
[48]	2021	Gearbox faults	Simulated faults are induced in a real WT considering damage in the main bearings, broken tooth, and gear wear of a planetary gearbox.	Planetary gearbox: outer race fault, inner race fault, inner-

				outer race fault, ball's fault, gear wear, broken tooth.
[31]	2021	Rotor-blades faults	Raindrops can induce fatigue to the WTs blades by impact erosion.	Blade coating fatigue.
[33]	2007	Rotor-blades faults	Dust in the wind cause changes in the rotor-blade surface roughness by particles accumulation.	Blade surface roughness modification.
[35]	2021	Rotor-blades faults	Low temperatures cause erosion of leading-edges and protective coating in rotor-blades.	Blade leading-edge coating erosion.

As seen from table, the most frequent faults according to the number of works reported in the literature rely in the following components of WTs: the generator, the power converter, the gearbox, main gearings, and turbine blades. Although there exist other elements that integrate the WP generation system, they have not been addressed due to the particularity and complexity of the system. This means that some subsystems of HAWTs and VAWTs are very particular. Hence, a generalized approach for fault diagnosis cannot be proposed as in the classical fault studies.

5. Current Methodologies for Fault Diagnosis in WP Generation Systems

In the last section, several works were analyzed to define the most frequent faults studied in the literature of the WP generation systems, which leads to considering what solutions have been proposed to identify and diagnose such fault conditions. Therefore, this section will address the state-of-the-art regarding the proposed methodologies for identification and fault diagnosis, better known as fault detection and diagnosis methods (FDDMs) [43], in the HAWTs and VAWTs. In the reported work, the FDDMs can be divided in three main groups: model-based, knowledge-based, and data-driven [43,148]. Model-based FDDMs require a mathematical representation, or a parameterized model, of the system [153]. Knowledge-based FDDMs need the expertise knowledge about the system analyzed, sometimes these methods are named signal-based because the techniques used to treat the signals require such knowledge [154]. Data-driven FDDMs make use of statistical analysis or data mining to perform the diagnosis, and their results depend directly on the data quality [155]. At the end of the section, a table will be presented summarizing the reported methods considering type of FDDM, fault addressed, techniques used, and accuracy reached. However, in the next lines, several works reported in the literature will be described detailing the methodology used for the fault detection and diagnosis (FD) in the electrical and mechanical components of WTs.

Before starting the in-detail revision of the methodologies for the fault detection in WP generation systems, it is important to mention that, as in the case of SPV systems, these types of installations are highly exposed to the presence of surges due to lightning events. In fact, the standard IEC 61400-24 defines the criteria that must be met for every lightning protection system (LPS) in wind generation [156]. The higher the WT is located, the greater the probability of being struck by lightning. Therefore, the high-power wind generator are more prone to result hurt [157]. Moreover, due to their geometry and location, the blades of the WTs are the most exposed parts, and they are constantly damaged by the action of lightning resulting in unexpected outages in the generation process. According to [158], a conventional LPS can be divided into three parts: an external lightning protection system, an internal lightning protection system, and the grounding system. The external protection system is the part of the LPS that is in direct contact with the lightning, and it composed of an air-termination system and a down conduction system to conduct the current to the ground. The internal lightning protection system is composed of an equipotential bonding that considers the correct selection of the cables, the separation between conductors, the routing and shielding, as well as surge protection devices. Finally, and as is well-known, there is the system in charge of dissipating the discharge currents, avoiding hazards. All these elements must work together to achieve a reliable and efficient

LPS. The use of these protection systems must be considered before the wind farm starts working and its implementation may prevent some fault conditions in the blades, nacelle, and tower of the wind generator. Notwithstanding, there are many other sources of faults in WP generation systems and they can be treated using the techniques described below.

5.1. FDDM Regarding Electrical Components of WTs

Regarding the FDDM proposed for faults present in electrical components of WTs, the work presented in [49] analyses power converters when the available data from SCADA are insufficient, or with a small-scale. Therefore, to overcome this drawback, the authors proposed a methodology that integrates the parameters-based transfer learning (PBTL) and the convolutional autoencoder (CAE). The general procedure consists in transferring information from a similar WT to a target WT with the aim of using the information about the failure's properties. The data used come from a SCADA system considering real conditions. The component with the highest frequency was the power converter system and the accuracy achieved by this approach was of 97.7% in the fault prediction.

In relation to problems in the generators of WTs and the proposed approaches for FDD, several works have handled this issue. For instance, in [150], a data-driven approach is proposed for monitoring the generator conditions of offshore WTs. The approach first applies a processing of data coming from a SCADA system consisting in data re-sampling, outlier treatment, removal of redundant information, and extraction of the optimal k-best features. Later, an ensemble model of the extreme gradient boosting (XGBoost) framework is applied for estimating and predicting the state conditions of the system. In counterpart, SCADA systems could also generate large volume of data with multivariable time series having high spatio-temporal correlations that are a challenging task. Here, the research presented in [159] handled this drawback by proposing a spatio-temporal fusion neural network scheme to generate fault condition labels. First, feature extraction is performed considering spatial and temporal features through a multi-kernel fusion convolutional neural network (MKFCNN). The MKFCNN uses multiple convolution kernels of different sizes and learns about multi-scale spatial features; it also reduces the number of parameters required for training. Later, a long short-term memory (LSTM) scheme obtains the correlations among the spatial features extracted. Finally, the classification of fault conditions is made by means of a SoftMax classifier achieving average accuracies of 97.6% and 93.8% for historical dataset and real SCADA values, respectively. Meanwhile, the relationship between SCADA data of wind speed, turbine ambient temperature, and generator temperature by means of a sensor model (SM), or parameterized model, for FDD in WTs is studied in [160]. The parameters of the model provide information related to the fault, and these parameters are updated every day by using an estimation procedure to reflect changes in the relationship in real time. Then, the parameters of the model are taken, or extracted, e.g., sensitive features, using a nonlinear output frequency response function (NOFRF). The validation of the model is performed on three WTs, identifying generator faults related to rotor winding short circuits.

In addition, when WTs reflect power loss faults, some methodologies, as in [161], apply FDD for WTs based on fuzzy logic systems (FLS) and artificial neural networks (ANN). Thus, the ANN constructs the membership functions considering SCADA data and application environment, so the wind speed and active power are measured to construct the FLS. Posteriorly, SCADA data are grouped to calculate average values and the error is obtained between measured and predicted data. Hence, error and average values are input to the FLS with extended data-driven membership functions for detecting changes in the system that can be considered as anomalies. By its part, the single-phase-to-ground fault is studied in [40] by developing a resonance model of a wind farm with distributed parameters. Later, the correct lines from the collector wires are selected to identify the fault through a method based in Dempster–Shafer theory (D-S T). Then, two strategies for isolating faults are proposed to avoid overvoltage: gradual tripping of WTs and installation of a breaker at the WTs side. The proposed scheme achieves an accuracy of 99.6% for the correct line selection with the faults.

Finally, some problems of the pitch control system are treated in [162] for a spar-type floating WT model, focusing on the faults of the pitch sensor (bias value and fixed output) and the directional control valve (excessive friction, slit lock on spool, wrong voltage, and circuit shortage). The proposed scheme uses a Kalman filter (KF) to estimate the pitch angle and the valve spool position. Then, a residual signal between the estimated and the measured output is compared with a threshold to identify conditions changes in the system. Next, the KF output is fed to an artificial neural network (ANN) for performing the diagnosis, achieving an accuracy of 98%.

5.2. FDDM Regarding Mechanical Components of WTs

Regarding the FDDM proposed for faults present in mechanical components of WTs, many investigations have addressed the problems of the gearbox. For example, the work in [44] uses a statistical approach based on the Wilcoxon rank sum test (WRST) for detecting and categorizing fault conditions: abnormal operation, fault in the gearbox, and normal condition. This approach is applied in statistical hypothesis tests for the fault conditions and the normal operation is the null hypothesis, achieving a 95% of confidence level for the detected fault. Furthermore, a novel scheme based on data-driven FDD of gearboxes is presented in [48] using two techniques, the refined time-shift multiscale fluctuation-based dispersion entropy (RTSMFDE) and the cosine pairwise-constrained supervised manifold mapping (CPCSMM). The RTSMFDE generates a high-dimensional set of features that is reduced to a low dimensional representation through the CPCSMM. Then, the classification is performed in simulations through a beetle antennae search-based support vector machine (BAS-SVM) with an 100% of accuracy reached. Likewise, a scheme for performing FDD of gearboxes through a multi-channel convolutional neural network (MC-CNN) on a benchmark model considering a 5 MW WT is presented in [152]. This scheme first converts the time-domain signals acquired from the system into images. Posteriorly, the images are processed by the MC-CNN applying multiple parallel local heads to observe the changes in every measured variable separately to detect faults of rotor imbalance and gearbox damage. The accuracy achieved by this scheme is of 99.85% for the database. Another scheme for FDD in gearboxes of a wind farm is developed in [155], where a relief series algorithm (ReliefF) extracts important information (features) regarding the system conditions from a SCADA data set. As the number of features extracted is of high dimensionality, a reduction is performed through the principal component analysis (PCA) avoiding information redundancy. Then, a deep neural network (DNN) performs diagnosis for single and for multiple faults, achieving accuracies in the diagnosis of 98.5% and 96%, respectively. Similarly, in [163], a methodology that combines the convolutional neural network (CNN), the long short-term memory (LSTM), and the attention mechanism (AM) is developed for differentiating anomalies in gearboxes during WTs operation. The analyzed data come from a SCADA system for being preprocessed. Thus, the CNN extracts main features from data, allowing the LSTM algorithm to learn the system operation, while the AM enhances the accuracy of the detection of faults. This methodology reaches a confidentiality of 97.7% based on the statistical indicator R^2. In this same field, the developed work of [164] proposes a method for diagnosis compound faults in WTs gearboxes. The approach uses the fast spectral kurtosis (FSK) for transforming the measured signal from a vibration sensor into a two-dimensional image named fast kurtogram. After that, a multi-branch convolutional neural network (MBCNN) takes the image of the FSK as an input feature map for selecting the optimal branch for the convolutional stage, finally yielding the output fault pattern. The validation of the method achieves 90% and 97% of accuracy in the diagnosis for signals with and without noise, respectively. Finally, FDD in planetary gearbox bearings for WTs by using an enhanced sparse representation-based intelligent recognition (ESRIR) is tackled in [165]. Here, a first stage design is structured using dictionaries by means of an overlapping segmentation strategy through measurements of vibration sensors, taking advantage of the periodic self-similarity and shift-invariance property of planetary bearings. At a second stage, fault recognition is achieved by a sparsity-based diagnosis strategy using a minimum sparse reconstruction error criterion. The scheme obtains between 99.9% and 100% of accuracy for the considered conditions.

By the other part, the FDD applied over the rotor-blades of WTs shows works that have proposed some approaches, like the study presented in [31] that describes a computational framework to model the wind turbine blade coating fatigue caused by raindrop impact. The analysis presents a stochastic rain field simulation (SRFS), considering the size, impact speed, impact angle, and different raindrop shapes, e.g., spherical, flat, and spindle. Later, the raindrop impact stress is computed through the smooth particle hydrodynamics (SPH). Then, the analysis of coating fatigue modeling is performed through the mass-loss-rate (MLR) increasing period, reaching 97% of accuracy in the model prediction. In this same line, the fault conditions of WTs blades are also analyzed in [43] by means of a data-driven approach adopting a SCADA system. In this study, the proposal integrates a hybrid FDD approach based on three techniques: generalized regression neural network ensemble for single imputation (GRNN-ESI), recursive principal component analysis (RPCA), and wavelet-based probability density function (PDF). The GRNN-ESI is applied to impute the noise and missing data. Then, RPCA performs dimensionality reduction from the dataset to obtain meaningful features, and PDF detects incipient faults in blades with an accuracy of 88.7%. Otherwise, the work developed in [153] presents a mixed model-based and a signal-based FDD for rotor-blades of floating offshore WTs. The model-based scheme uses the fault detection and approximation estimator (FDAE) and the fault isolation estimator (FIE) for detecting and isolating faults in the system. Then, the signal-based method uses the frequency domain analysis through short time Fourier transform (STFT) and a K-nearest neighbor (KNN) classifier for detecting and isolating mooring lines faults. The validation is made for a 10MW WT benchmark implemented in Simulink. Additionally, the problems caused by icing in rotor blades is tackled in [166] where a scheme that handles data characterized by sets of high dimensionalities, data imbalance, and differences in statistical distributions is proposed. In general, the analyzed data from SCADA are preprocessed with re-sampling and normalizing. Later, data are divided for model construction and model verification. The model construction considers subsets for training and testing, and here the machine learning algorithm K-nearest neighbor (KNN) and transfer learning algorithm TrAdaBoost are applied. The TrAdaBoost reaches above 99% of accuracy in the diagnosis.

Addressing the FDDMs focused on bearing faults, the investigation described in [151] develops a methodology based on a hybrid attention improved residual network (HA-ResNet) for diagnosing faults in the main bearings of WTs. First, the wavelet package transformation (WPT) is applied to highlight the main band frequencies of the wavelet coefficients. Later, the extraction of features is improved by a channel attention framework for the diagnosis, so, the proposal achieves a 98.79% of accuracy for simulated drivetrain and real data from a wind farm. Moreover, the study in [167] addresses the FDD for WTs rolling bearings by proposing an intelligent method based on three stages: feature extraction, dimensionality reduction, and pattern recognition. The extraction of features is performed through the multiscale permutation entropy (MPE) from the vibration signals of rolling bearings, yielding a set of features of high dimensionality. Since the MPE measures the complexity of time series detecting weak changes, then if rolling bearings have faults, their non-linear dynamic will change accordingly. The dimensionality reduction of features is performed through a manifold learning algorithm, named Mahalanobis semi-supervised mapping (MSSM), to overcome the problems of Euclidean distance. Thus, the pattern recognition of faults is conducted by means of a heuristic approach known as the beetle antennae search (BAS) that optimizes the parameters of a support vector machine (SVM) reaching a 100% of diagnosis accuracy.

At last, but not least, some other problems of diverse nature must be considered to define alarms that allow the WTs keep at safe ranges. In this sense, the work in [168] addresses the frequent principal fault detection and localization (FPFDL) approach. This approach first applies an improved oversampling algorithm to generate and develop the balanced data from the imbalanced dataset of real wind farms. The oversampling is achieved through a synthetic and dependent wild bootstrapped oversampling technique (SDWBOTE) that combines the dependent wild bootstrap (DWB) and a modified synthetic minority oversampling technique (SMOTE). Finally, a one-dimensional convolutional neural network (1D-CNN) model based on FPFDL automatically extracts features from the pre-processed data for fault identification with 99% diagnosis accuracy.

Table 4 presents a summary of the previously discussed works presenting them in two branches of FDDMs regarding electrical and mechanical components. Into this division, the works are depicted indicating the year, the fault handled, the type of methodology (model-based or data-driven), the techniques used or integrated, and the accuracy reached, if available.

Table 4. Summary of the reported FDDMs.

FDDM Regarding Electrical Components					
Ref.	**Year**	**Fault**	**FDDM**	**Techniques**	**Accuracy**
[49]	2021	Power converter faults	Data-driven	CAE + PBTL	92.5%
[150]	2021	Generator faults	Data-driven	XBoost	---
[159]	2020	Generator faults	Data-driven	MKFCNN + LSTM + SoftMax	93.8%
[160]	2020	Generator faults	Model-based	SM + NOFRF	---
[161]	2020	Loss power generation	Data-driven	ANN + FLS	---
[40]	2018	Sigle-phase-to-ground fault	Model-based	D-S T	99.6%
[162]	2021	Pitch control system faults	Model-based	KF + ANN	98%
FDDM regarding mechanical components					
Ref.	**Year**	**Fault**	**FDDM**	**Techniques**	**Accuracy**
[44]	2020	Gearbox faults	Data-driven	WRST	95%
[48]	2021	Gearbox faults	Data-driven	RTSMFDE + CPCSMM, BAS + SVM	100%
[152]	2021	Gearbox faults	Data-driven	MC-CNN	99.85%
[155]	2021	Gearbox faults	Data-driven	ReliefF + PCA + DNN	96–98.5%
[163]	2021	Gearbox faults	Data-driven	CNN + LSTM + AM	97.7%
[164]	2021	Gearbox faults	Data-driven	FSK + MBCNN	90–97%
[165]	2021	Gearbox faults	Data-driven	ESRIR	99.9–100%
[31]	2021	Rotor-blade faults	Model-based	SRFS + SPH + MLR	97%
[43]	2020	Rotor-blade faults	Data-driven	GRNN-ESI + RPCA + PDF	88.7%
[153]	2021	Rotor-blade faults	Model-based	FDAE + FIE and STFT + kNN	---
[166]	2021	Rotor-blade faults	Data-driven	TrAdaBoost + TL	99.1–99.8%
[151]	2021	Bearings faults	Data-driven	HA-ResNet + WPT	98.79%
[167]	2020	Bearing faults	Data-driven	MPE + MSSM + BAS-SVM	100%
[168]	2021	Diverse nature faults	Data-driven	SDWBOTE + CNN	99%

At this point, it becomes relevant to make some clarifications. First, it has been previously mentioned that the machine learning implementations are very promising in the field of condition monitoring of electric systems such as SPV and WP generators. In this sense, most of the works presented in this section that adopt a data-driven approach also use machine learning methods [49,155,159,167]. This situation reinforces the fact that machine learning is a versatile tool that can be adapted to solve a wide variety of problems. Therefore, the role of the machine learning in the fault detection in WP generators consists in characterizing the system, detecting deviations from the normal operating conditions, and classifying the fault that is present in the system. This promises to be of great help for the operators around the world that will be allowed to perform a diagnosis even without having an in-depth knowledge of al the theoretical principles involved in SPV and WP generation systems.

Moreover, as in the case of SPV systems, it is common to fuse different techniques for the condition monitoring of WP systems in order to improve the results delivered by each methodology separately. An example of this situation is presented in [155] where the statistical analysis is combined with the AI to obtain a machine learning approach that can identify mechanical faults with high accuracy. Additionally, in [48], heuristic algorithms are combined with SVM and they also prove to be effective for the detection and classification of faults in a WT. Therefore, composite methods represent a very popular solution for the condition monitoring of WP generation systems since they help to improve the accuracy in the detection of specific faults. These methodologies are expected to continue providing reliable and robust solutions for the renewable generation industry by facilitating the maintenance and reducing the unexpected stops in the production due to faults.

6. Prospective and Tendencies in the Emerging Methods for Monitoring Systems and Fault Diagnosis Regarding Renewable Power Generation Based on SPV and WTs

In this section, the prospects and trends of SPV systems and WPG systems will be discussed. The main purpose of this discussion is to highlight the areas of opportunity considering possible contributions of future methodological developments in both the faults of the systems (SPV and WPG) and FDDMs.

6.1. Prospective and Trends for SPV Systems Studies

It is clear that SPV systems have highly evolved and they are capable of supplying a good part of the energy requirements of modern society. Notwithstanding, right now, it is hard to believe that in the context of an electrical system constituted only for renewable energies. More important than the fault detection, already a well-studied field, it is necessary to develop efficient and reliable strategies for dealing with the variability of the natural resources as sun and wind. Nowadays, the energy storage systems try to fulfill this need. These energy storage systems are primarily based on batteries and capacitors, but these elements remain sensitive and inefficient. Therefore, an important part that is expected to find relevance is the monitoring and diagnosis of energy storage systems. This task is already performed, but mainly at a small scale. The development of large-scale storage systems is likely and it will be essential to count with devices and strategies that guarantee the correct operation and maintenance of such systems.

Additionally, and in the light of this research, it is noticeable that most of the current methodologies for fault detection in SPV systems focus on the detection of faults on the DC side of the system. Problems associated with the SPV panels, e.g., partial shading, dust accumulation, hot spots, and bypass diode faults, are vastly treated in the literature. The same situation occurs with the faults related with the interconnection among SPV panels where line-line faults, line to ground, arc faults, open circuit, and short circuit faults are highly boarded. This is not a weird situation considering that all the generation process is carried out in DC and then the energy is converted into AC by means of an inverter. In this sense, if the electric generator (the SPV panels in this case) fails, the inverter is unable to take some action to continue with the generation process. This is why it is important to pay special attention in the operation of the SPV panels and their interconnections. Notwithstanding, the inverter plays a major role in terms of efficiency, reliability and quality of the supply. The power quality is still a hot topic, and several concerns related with this issue appear when speaking of renewable energies. In this sense, a marked trend in SPV systems consists in the design of new topologies for power inverters that increase the quality and reliability of the power supply. These designs include reactive power compensators, high speed switching devices, harmonic filters, and some other modules that pretend to increase the quality in the energy conversion process. Therefore, more attention must be paid to the monitoring of inverters and problems in the AC side of the system since all of the equipment that is connected to the grid, at industrial and residential levels, operates with AC and a low quality causes damages to the loads that reduces their lifetime and generates unexpected stops in industries, representing financial loses.

Finally, there is a wide variety of algorithms that deliver good results for the identification and classification of different faults in SPV systems, but the most recent strategies are mainly based on the use of machine learning. This is a tendency that is expected to continue because of the versatility of these techniques. The main advantage of the machine learning techniques is that they can work with a broad type of inputs that go from weather conditions and electrical signal to images. In this sense, the upcoming methodologies are expected to be hybrid approaches that fuses the advantages of different areas. For instance, signal analysis based on space transforms, e.g., Fourier transform, wavelets, and empirical mode decomposition, can work along with statistical analysis-based techniques and with AI-based classifiers to perform an accurate and reliable monitoring of the condition of any system. Such methodologies have been widely explored in other areas of the engineering and they have started to being used in the fault detection and classification in SPV systems. These schemes present a high adaptability to new conditions making them robust and efficient. Moreover, the new trends of novelty detection and transfer learning are strategies becoming popular in some fields of science and engineering that have the potential to be useful in the condition monitoring of SPV systems.

6.2. Prospective and Trends for WPG Systems Studies

The revision of the reported literature makes it clear that wind power is today, and will remain in future, a very important source of renewable energy that faces important changes and a rapid development. The design and development of new WP generation technologies has allowed to install a wide variety of WTs that match with some classifications seen in previous sections. Nevertheless, they are still prone to fail due to environmental adversities, malfunctioning, as well as aging and wearing due to their operation through the time. As seen from the revision of the reported works, there are several elements that integrate the WTs. However, the main elements that have been addressed for research are the generator, the power converter, the gearbox, the main bearings of the drivetrain, and the rotor-blades. This fact does not imply that the rest of the elements on the WTs are less important, it simply reflects that much effort and research has been focused on such elements because of their importance and effects in the final power generation capacity, maintenance, and costs. Now, it was also observed that the faults that are most commonly analyzed and diagnosed are precisely of the variety of problems associated to the elements previously mentioned, i.e., generator short-circuits, wiring faults, power loss, hardware heating of the converter, broken teeth of gear, damage in the rolling bearings, and in general aging, wear, and corrosion of mechanical elements. Perhaps it is worthwhile to mention that many of the faults studied can be simulated in the physical WTs, in other cases through test benches, or the authors could access historical datasets, or model using a benchmarking framework. This gives the general perspective that such faults are still going to be studied since technological developments concerning WTs will continue to be seen in new contexts of application, installation, and environments, among others. However, there also exists an area of opportunity in those elements and their associated faults that has not yet been completely explored and exploited due to the inherent complexity or particularity.

In relation to the FDDMs, it can be said that some years ago the proposed solutions for FDD use to rely on the signal-based and knowledge-based schemes, where the focus was on measuring and monitoring signals coming from sensors like current, voltage, temperature, encoders, and vibrations. Such approaches used to pre-process and process the measured signals by means of some space-transformation technique to analyze the resulting information in a particular domain: time, frequency, or time-frequency. However, some limitations and drawbacks, e.g., non-linearities, datasets of high dimensionality, multiple or combined conditions, among others, have prompted investigations to look for new approximations with better benefits. Thus, as an alternative solution, the model-based methodologies have been considered for performing FDD for any type of WT technology since a physical system is not required. Moreover, a hybrid approach model-prediction and physical system can be used, but the main disadvantage of these approaches is the inherent inaccuracy when system conditions change. Therefore, a clear tendency in the adoption and development of data-driven methodologies is highly noticeable, as seen in Table 2. In this sense, most of the current works used machine learning and deep learning techniques for solving the FDD problem. It is also remarkable for data-driven schemes that the classical space transform techniques, e.g., STFT, WPT, FLS, etc., are commonly used for data pre-processing, while techniques, such as TL, PCA, LSTM, etc., perform feature extraction and dataset reduction, and variants of ANN, e.g., DNN, CNN, or SVM, etc., perform fault classification.

Up to now, most investigations have been performed on the common HAWTs for both onshore and offshore installation due to the reliability, maintenance, and cost. However, currently, these WP generation systems are facing major challenges in terms of power generation capacity in the large-scale range, and new investigations are moving towards VAWTs due to the technological gap limiting these technologies being reduced. Therefore, this situation also represents an area of opportunity since the design, modeling, implementation, and study of VAWTs remain complex and underexplored, but with the new advances in software modelling, the machine learning implementations, and deep learning techniques, it is possible to explore solutions for these systems.

7. Conclusions

This paper presents a general overview of the two main renewable energy generation systems, namely the SPV and the WP, regarding two main topics of interest: faults present in the generation system and the proposed methodologies for fault identification. Since the SPV generated energy reaching a global capacity of 760 GW and the WP generated energy reaching an accumulative global capacity of 837 GW, it is very important to keep these systems in optimal operation conditions, and for that reason fault detection and diagnosis are of such importance in this work. Therefore, the first aspect considered in this review was to present an analysis of the most frequent faults present in both the SPV and the WP. In summary, the faults present in the SPV systems can be classified as temporary faults and permanent faults. Thus, the temporary faults are related with the weather conditions, e.g., cloud presence, partial shadowing, and dust accumulation. In the case of the permanent faults, a study considering early, extrinsic, and deterioration faults can be performed. By its part, the faults present in the WP generation systems can be divided in two main branches, namely faults related to electrical components and faults related to mechanical components. On one side, the faults related to the electrical components in turn are those that affect the performance of an electrical element of a WT, such as the generator or the power converter. On the other side, the faults related to mechanical components are those that affect some mechanical part, such as the gearbox, the main bearings, or the rotor-blade. All the faults analyzed in this review affect main aspects of the operation condition in the SPV and WP generation systems, e.g., reducing their power output capacity, disrupting maintenance actions, and increasing the operation costs. Therefore, as a complement and to provide a solution to these problems, several methodologies have been reported in the literature for performing fault detection and diagnosis. It is very interesting how in both SPV and WP the tendency in the investigations is towards the use of data-driven methodologies that implement machine learning and use deep learning techniques. It worthwhile to mention that the general current schemes for fault detection and diagnosis imply in general five main steps: data acquisition, data pre-processing, features extraction, feature dimensionality reduction, and classification. There exist several areas of opportunity regarding the energy generation systems, specifically considering fault detection and diagnosis. For instance, there are few works of WP generation systems that handle elements, other than generators, power converters, gearboxes, and blades, that have not been deep explored. Besides, although the data-driven approaches are used with most frequency today, there are still drawbacks, limitations, and optimizations that need to be considered, and the combination of techniques in the five main steps previously mentioned still requires attention.

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Nomenclature

CAE	Convolutional Auto-Encoder	PBTL	Parameters-based Transfer Learning
XBoost	Extreme Gradient Boosting	LSTM	Long Short-Term Memory
ANN	Artificial Neural Networks	FLS	Fuzzy Logic System
WRST	Wilcoxon Rank Sum Test	BAS	beetle antennae search-based
PCA	Principal Component Analysis	DNN	Deep Neural Network
FSK	Fast Spectral Kurtosis	AM	Attention Mechanism
MLR	Mass-Loss-Rate	ReliefF	Relief series algorithm
FIE	Fault Isolation Estimator	kNN	K-Nearest Neighbor
TL	Transfer Learning	STFT	Short Time Fourier Transform
MKFCNN	Multi-kernel Fusion Convolutional Neural Network	D-S T	Dempster-Shafer theory
MC-CNN	Multi-Channel Convolutional Neural Network	KF	Kalman Filter
RPCA	Recursive Principal Component Analysis	SM	Sensor Model
FDAE	Fault Detection and Approximation Estimator	SVM	Support Vector Machine
RTSMFDE	Refined Time-Shift Multiscale Fluctuation-based Dispersion Entropy	CNN	Convolutional Neural Network
CPCSMM	Cosine Pairwise-Constrained Supervised Manifold Mapping	SPH	Smooth Particle Hydrodynamics
ESRIR	Enhanced Sparse Representation-based Intelligent Recognition	PDF	Probability Density Function
GRNN-ESI	Generalized Regression Neural Network Ensemble for Single Imputation	WPT	Wavelet Package Transformation
HA-ResNet	Hybrid Attention Improved Residual Network	MPE	Multiscale Permutation Entropy
SDWBOTE	Dependent Wild Bootstrapped Oversampling Technique	NOFRF	Nonlinear Output Frequency Response Function
SRFS	Stochastic Rain Field Simulation	MBCNN	Multi-Branch Convolutional Neural Network

MSSM	Mahalanobis Semi-supervised Mapping

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