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Review

A Review of Smart Photovoltaic Systems Which Are Using Remote-Control, AI, and Cybersecurity Approaches

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Abstract: In recent years, interest in renewable energy and photovoltaic systems has increased significantly. The design and implementation of photovoltaic systems are various, and they are in continuous development due to the technologies used. Photovoltaic systems are becoming increasingly complex due to the constantly changing needs of people, who are using more and more intelligent functions such as remote control and monitoring, power/energy prediction, and detection of broken devices. Advanced remote supervision and control applications use artificial intelligence approaches and expose photovoltaic systems to cyber threats. This article presents a detailed examination of the applications of various remote-control, artificial intelligence, and cybersecurity techniques across a diverse range of solar energy sources. The discussion covers the latest technological innovations, research outcomes, and case studies in the photovoltaics field, as well as potential challenges and the possible solutions to these challenges.

Keywords: photovoltaic systems; remote control; AI; cybersecurity

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1. Introduction

The modern revolution is directly associated with the generation, consumption, and conversion of electrical energy due to the inventions from the last decades which have improved the quality of human life [1]. In the last decades, people have started to replace fossil fuel devices with environmentally friendly devices that use renewable energy. Photovoltaic systems are environmentally friendly and can be used all over the world, especially in isolated areas. It can be observed that the main growth of photovoltaic applications and publications comes from the Asia–Pacific and Middle East North Africa (MENA) regions [2]. These regions are characterized by a hot and dry climate with lots of sunshine all over the year. In paper [3], the researchers preconize that Asia will dominate the solar photovoltaic market with around 57% of global photovoltaic installations, followed by North America (21%) and Europe (11%), by 2050.

The reliability of a photovoltaic system is a crucial factor in its performance, so it is necessary to consider the following factors when designing a photovoltaic system [4]: system location, the climate where the system is installed, the available budget, the technical characteristics of used devices, and how best to respect the laws and regulations. Additionally, it is important to consider the monthly and annual electricity consumption to ensure the necessary energy production for daily needs. To ensure energy production for human needs, different types of PV systems are proposed in the literature. In paper [5], a system with a specific configuration was presented and its behavior was analyzed. The system designed was in Rome, and it was a grid-connected system which was suitable for a house used by a family with four members. The photovoltaic (PV) system had 3 kWp of electrical power and generated 4350 kWh electricity per year. The energy produced during sunlight periods was stored in batteries and used latter when the energy production stops. The batteries represented a risk of explosion and fire. According to paper [6], Li-ion batteries are very sensitive and the fire from a cell can spread rapidly to other cells, causing major damage. In paper [7], the researchers described the operational mode of a hybrid photovoltaic system and its financial impact. It could be observed that there was a significant difference between the imported and exported energy using two different tariffs.

Due to the evolution of technology, the humans want to use modern applications for remote monitoring and control, which includes using artificial intelligence approaches for energy prediction and cybersecurity measures for safety. Artificial intelligence concepts (big data, machine learning, neural network, and deep learning) are used in cell defect detection [8], in the supervision of photovoltaic systems [9], and to forecast the energy produced by PV systems [10]. Zahran et al. [11] presented how artificial intelligence algorithms are applied in the photovoltaic domain. Smart applications for monitoring photovoltaic systems store collected data and, based on them, can predict the energy/power production on a sunny, rainy, or cloudy day using AI algorithms. Additionally, these applications offer remote access and real-time responses.

The monitoring of photovoltaic systems is necessary because various environmental factors (temperature, irradiance, wind speed, shading, and dust and dirt) change their values during the day and influence the operation and functionality of solar systems. A monitoring system has the role of observing and recording a system's parameters in real-time. Modern tracking solutions improve a system's efficiency, provide updated information, and execute preventive measurements in the case of flaw detection [9]. Monitoring systems are capable of notifying users when an unplanned event occurs [9]. In the past, the monitoring of photovoltaic systems used wired systems (RS232 cable or RS485 cable) for transferring data [12]. These cables carrying data are exposed to environmental conditions [13] (snow, rain, humidity, temperature, etc.). In contrast, wireless monitoring solutions offer less environmental exposure compared to wired ones. Wireless solutions have faster decision-making, low maintenance costs, and higher response times, and they present increased mobility and network security methods [9].

A control system aims to act immediately after an unplanned event. The verification of a photovoltaic system can be done [11] physically by using cables or wirelessly by using Bluetooth or Wi-Fi connections. The monitoring and control of a system play a crucial role in ensuring the proper functioning of the photovoltaic system. In the research [14], the control part was not detailed enough as the paper primarily focused on the system's tracking approaches. In paper [11], the Internet was used to transfer the collected and controlled data using LabVIEW Web Server functions.

To maintain the safety of PV systems, the applications that monitor and remotely control photovoltaic systems should adhere to the three main cybersecurity principles: confidentiality, integrity, and availability of data. According to paper [15], photovoltaic systems are vulnerable to cyber-attacks. According to Muhammad et al. [16], researchers tried various types of cyber-attacks against a photovoltaic system using a simulated microgrid.

The aim of this research is to review remote-control solutions for PV systems, AI techniques applied in PV systems, and cybersecurity techniques. Our research contributions are as follows:

- Analyzing different implementations of PV systems.
- Reviewing the literature on the remote control of PV systems.
- Reviewing the literature on AI techniques and methods applied in photovoltaics.
- Reviewing the literature on cybersecurity threats and vulnerabilities in smart PV systems and cyber-attacks on power systems.
- Discussing the architecture of PV systems and how they can be implemented easily, efficiently, and securely using remote-control, AI techniques, and cybersecurity methods.

This research paper consists of the following sections: The methodology used for the research is presented in Section 2, the configurations of PV systems are presented in Section 3, the implementation and remote-control methods are discussed in Section 4, Section 5 presents AI methods used in PV systems, Section 6 presents the vulnerabilities and threats to which PV systems are exposed, discussions about the architecture of the PV systems are in Sections 7 and 8 presents the conclusion.

2. Methodology

In order to guarantee the inclusion of the most reliable evidence and the identification of all pertinent studies, we have elected to adopt a systematic approach throughout the course of our research. The process entailed a comprehensive search strategy, meticulously executed in accordance with the literature search guidelines delineated in reference [17] and the recommendations for the Preferred Reporting Items for Systematic Reviews (PRISMA) outlined in reference [18].

At the beginning, a search was made in the ScienceDirect database to identify relevant scientific literature. The ScienceDirect database was chosen because it provides access to research articles and journals from leading academic publishers and a systematic evaluation of the literature can be conducted easily. The search only included English-language documents and there were no restrictions on their geographical distribution, but the emphasis was for scrutinizing literature that was published from 2014 until 2023 to ensure the relevance and accuracy of the data.

To perform the search query, specific keywords were used in the title, abstract, and keywords fields of the documents (Figures 1–3). Firstly, the relevance of the research for PV systems was crucial. Research studies that addressed issues such as the efficiency and working mode of PV systems, integration of PV systems in daily life, and modern techniques for PV systems were particularly significant. In Figure 1, the evolution of published articles based on the keywords “photovoltaic system” is presented (ScienceDirect database). It can be observed that the number of published articles in 2022 and 2023 was almost the same and was almost 2.5 times bigger compared with the number of published articles in 2014. This means that people are more and more interested in developing and using photovoltaic energy for different needs.

Another important criterion is the integration of modern techniques in the photovoltaic field. In the context of the continuing development of the artificial intelligence field, AI algorithms are applied also in the PV field for detecting, monitoring, and controlling PV systems. These AI methods expose the PV systems to new threats, and cybersecurity measures are needed to protect the systems. Figure 2 presents the evolution of published articles based on the keywords “cyber-security for photovoltaic system” in the ScienceDirect database. It can be observed that the interest in the safety of photovoltaic systems has an ascendent trend. This means that people’s interest in photovoltaics is increasing, and new challenges have appeared, such as advanced monitoring and control techniques based on AI algorithms, and the risk of cyber-attacks is becoming bigger.

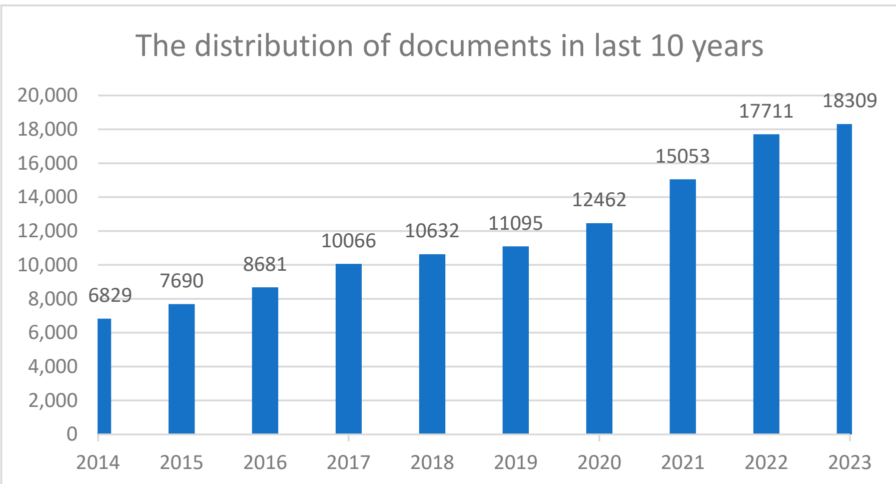

Figure 1. The number of published articles based on the keywords “photovoltaic system”.

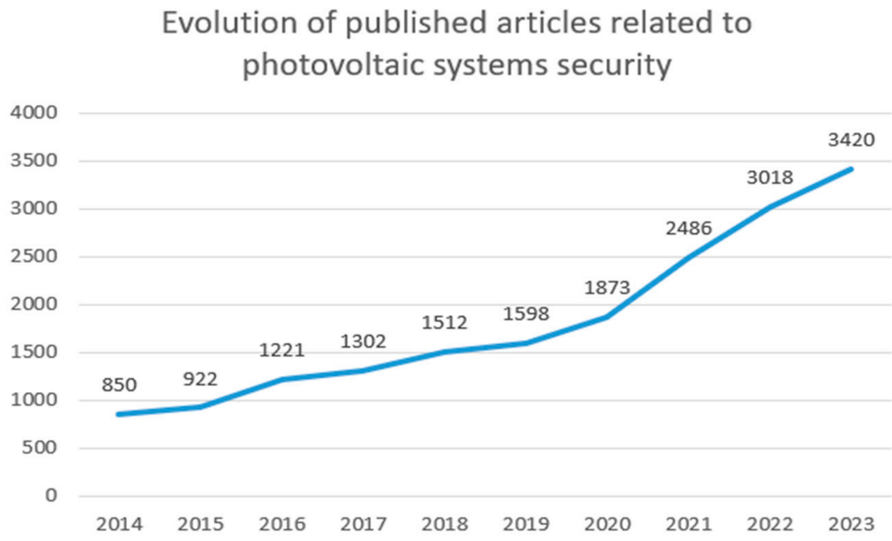

Figure 2. Evolution of published articles for photovoltaic systems' cybersecurity.

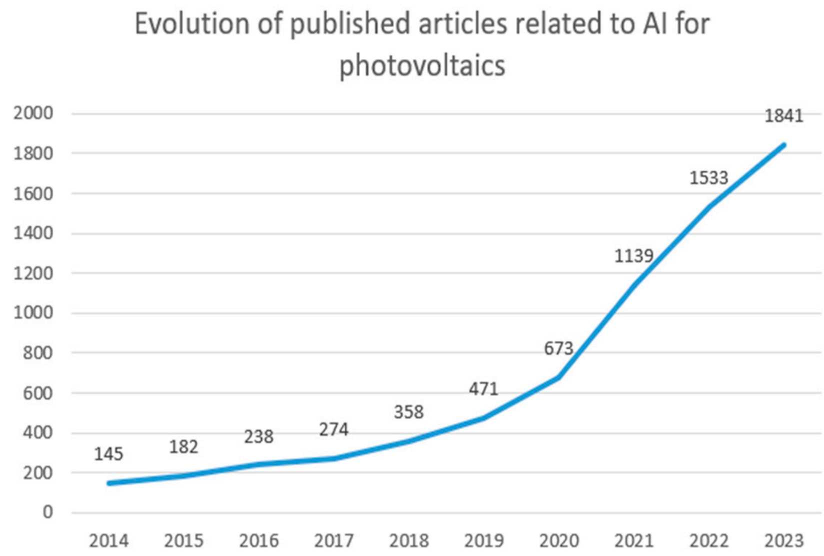

Figure 3. Evolution of published articles for AI in photovoltaics.

Figure 3 presents the evolution of published articles based on the keywords "artificial intelligence in photovoltaics" in the ScienceDirect database. It can be seen that the interest in using AI methods in photovoltaics has an ascendent trend, and people's interest in using smart algorithms in solar energy has increased in the last 10 years.

3. Modern Configuration of Photovoltaic Systems

Photovoltaic systems consist of different components based on people's needs. They can be classified by their configuration:

- On-grid system—the main parts are the solar panels, inverter, meter, and consumers. Figure 4 presents a logical scheme of an on-grid system.
- Off-grid system—the system stores energy in batteries, and the main parts are the PV panels, charge controller, inverter, batteries, and consumers
- Hybrid system—stores the produced energy in batteries, and when the batteries are fully charged, the produced energy is then inserted into the grid. The main parts of the hybrid system are the solar panels, batteries, inverter, and consumers.

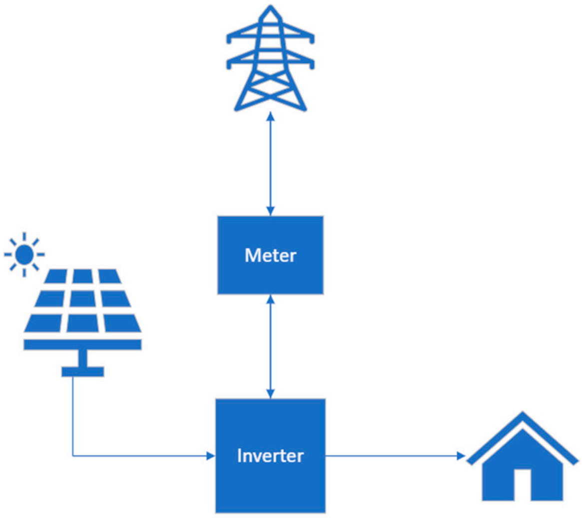

Figure 4. The logical scheme of an on-grid system.

An important device for on-grid systems is the inverter. This device has a double role: to convert DC-AC and AC-DC, and to interface the PV system with the grid using one-way or two-way communication. Over the years, researchers have designed and developed more models (multilevel inverters for three-phase AC line voltage, current and voltage inverters, and inverters which have machine learning functions) [9]. Because the behavior of photovoltaic systems is too hard to be predicted (sometimes impossible), modern inverters have intelligent functions, such as voltage regularization and frequency regularization [9].

Stand-alone photovoltaic systems (Figure 5) have the property of charging batteries, and the house's consumers use the energy stored in the batteries. The solar panels should have capability to charge the batteries during the day when there is sunlight. The stored energy will be used during the night or during cloudy or rainy days. In such systems, the battery capacity is very important and the sizing of the battery plays a crucial role.

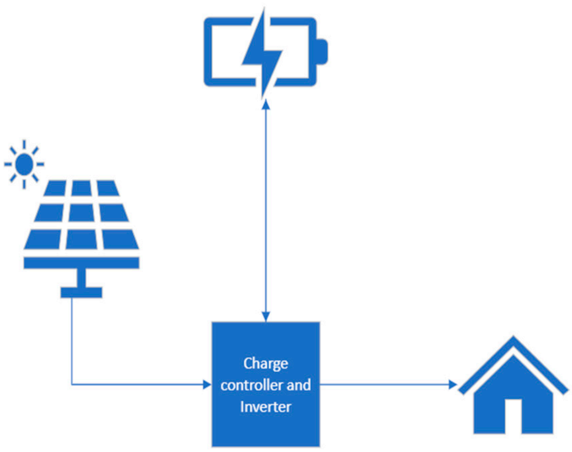

Figure 5. The logical scheme of an off-grid system.

It is necessary that more factors are taken into consideration when a battery is built, such as the energy consumed during the day (W), the energy consumed by the system's devices per day (W), the number of cloudy/rainy days (around 3 days), the battery's coefficient for discharging, and the battery's nominal voltage [4]. The energy consumption for individual load is represented by Wh and calculated using the following equation:

$$E_i = P_i * T_u \quad (1)$$

where Ei represents the energy demand per day of individual load (Wh), Pi represents the rating of individual load per day (W), and Tu is time of use of the load per day (h) [4].

On the market, are more types of batteries: lead-acid, nickel-metal-hydride, li-ion, etc. The batteries can be used for storing electrical energy for a short time (the electrical energy is distributed for 24 h) or for a long period of time (which assures the system's availability for a few days).

An important characteristic of a battery is the battery's capacity. It is measured in kilowatt-hour (kWh) or ampere-hour (Ah) at a constant discharge rate [1].

$$Ah_{bank} = E_t / V_{dc\text{-}sys} \times D_{aut} \times 1.25 \quad (2)$$

where Ah_{bank} is the battery's capacity, E_t represents the total energy, $V_{dc\text{-}sys}$ is the DC voltage of the system, and D_{aut} represents the number of autonomous days. Then, the obtained value is multiplied by a factor of 1.25, which will increase the capacity by 25% to allow for reasonable system expansion.

Batteries present a high risk for explosions and fires. It is recommended to avoid overcharging, low charging, overcurrent, short circuit current, or high temperatures. In one study [6], it was demonstrated that there are many techniques for fire suppression for li-ion batteries, but there could be additional chemical reactions which could cause damage.

According to Triki-Lahiani et al. [19], there are three main reasons why the capacity of battery degrades rapidly:

- the poor manufacturing of the batteries,
- the behavior of degraded batteries,
- the threshold of the charge controller to protect the battery against over-discharge.

Battery packs should contain an advanced Battery Management System (BMS) which has the role of dynamically monitoring the battery pack and ensuring the efficiency of the Battery Energy Storage System (BESS) [20].

Figure 6 presents the scheme for a hybrid photovoltaic system which uses battery storage and grid connection. It is a combination of the two PV system types described above, which reduces grid dependency and help the balance of electricity supply and demand.

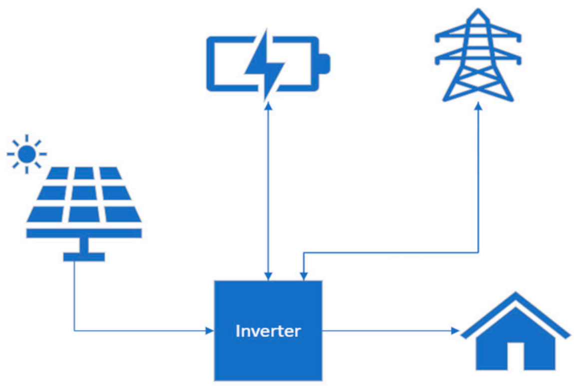

Figure 6. The logical scheme of a hybrid system.

The intelligent invertor plays a crucial role in hybrid systems by switching from grid connection (energy extraction or injection) to battery connection (charge or discharge the battery) and vice versa. During the sunlight period, the battery is charged. When the battery is fully charged, then the system introduces the energy to the grid. Even if the battery is discharged, the users have access to electrical energy and they are able to use it from the grid. The battery from a hybrid system should have the same mode of working as in a stand-alone PV system. In the hybrid case, the battery has a smaller capacity compared with the battery from a stand-alone PV system.

4. PV Systems—Implementation and Remote-Control Methods

First, several case studies for the photovoltaic systems are presented. In the selection process, the following aspects were taken into consideration: PV system implementation, system monitoring, and control methods which use AI and cybersecurity techniques. Each case study presents innovative implementations of different parts of the PV system.

Secondly, PV system control modes are described. Over the years, more control techniques have been developed for different parameters.

4.1. Use-Cases

Case 1: Deshmukh and Singh [21] proposed an installed a stand-alone solar photovoltaic (SA-SPV) system on the roof of a residential building and presented its results. The system was situated 12 m above the ground and had a tilt angle of 21°. The proposed system worked for three seasons specific to the India (Goa) region: southwest monsoon (June–September); post-monsoon (October–January), and summer (February–May). In addition, the system had a battery pack with a capacity of 300 Ah. The photovoltaic system proposed had two modes of operation: stand-alone and on-grid. Sometimes the consumers used the electrical energy from the grid, but in the summer months the system injected electrical energy into the grid. The system's behavior was beneficial for the house's consumers as they always had the necessary electrical energy for consumption.

The main risk of the proposed photovoltaic system is that the batteries have been placed in the building and the risk of the building being on fire increases [6]. The data acquisition was done remotely using the Combo platform which registered and stored the data in a memory card or in a cloud solution.

Case 2: Taghezoui et al. [22] considered data collected from a grid-connected photovoltaic system (GCPVS) plant in Algiers, consisting of 90 photovoltaic modules with a total power output of 9.54 kWp. The behavior of the GCPVS was simulated in MATLAB in order to obtain the anticipated evolution of the DC power produced by the photovoltaic arrays and the AC power at the output of the photovoltaic inverter. In the suggested approach, the temperature readings were not obtained through the monitoring system; instead, they were generated through a simulation process. Following a comparison of the simulation results with the measured parameters of the photovoltaic system, it was established that the Nominal Operating Cell Temperature (NOCT) model was an empirically validated and suitable representation of the system's behavior.

The main purpose of the paper is to present two ways for PV system monitoring: exponentially weighted moving average (EWMA) and double exponentially weighted moving average (DEWMA). Both proposed solutions detect faults of PV systems, especially anomalies occurring in the DC and AC outputs. Therein were discussed and investigated six types of electrical and environmental faults of photovoltaic systems. The proposed procedures are efficient, but they need improvements using modern techniques such deep learning-driven models [23].

Case 3: Emamian et al. [24] designed a stand-alone photovoltaic system for testing and analyzing the performance of an Intelligent Monitoring System (IMS). The photovoltaic panels powered three sensors, for temperature, humidity, and irradiance, which were installed on the panels. The data collected from these sensors were used for system monitoring and prediction of the output power.

The research presented a complex mode of operation and monitoring for photovoltaic systems. The monitoring system had many capabilities, such as using IoT applications, remote access, detecting (96.56%) and classifying (96.89%) faults, and power generation prediction in photovoltaic systems. The paper presented a comparison between the results obtained by the proposed model with other existing models (convolutional layer—Conv1d, multi-layer perceptron—MLP, LSTM) using two different metrics (root mean squared error—RMSE and mean absolute error—MAE).

The data transfer and user access were implemented by using cloud or Internet of Things (IoT) applications. The user's identity is not verified during the authentication process, and this could lead to leaking data to unauthorized persons. To avoid unauthorized access and leaked data, a MFA (Multi Factor Authentication) solution for user authentication could be implemented [25].

Case 4: Zhao et al. [26] presented an experimental configuration for the observation of parameter values in photovoltaic modules under four distinct fault conditions and in the absence of faults. The experimental setup comprised a photovoltaic system, a device for monitoring current and voltage, a controller, a signal transmission system, and an upper computer. The suggested monitoring solution is applicable to all types of photovoltaic systems and is based solely on the monitoring and evaluation of electrical parameters, including open-circuit voltage, short-circuit current, voltage, and current at the maximum power point.

The solution outlined in this research is more cost-effective and efficient than other existing solutions. It employs a smaller number of sensors and is capable of detecting a wider range of faults, including open-circuit, short-circuit, aging, and shadow shading faults, with high accuracy even in the presence of significant shading.

Case 5: Iksan et al. [27] developed a conventional hybrid photovoltaic system comprising 10 photovoltaic panels (with a 100 Wp capacity each), batteries, loads, inverters, maximum power point tracking (MPPT), PLN grids, sensors, and a monitoring system. The sensors were capable of connecting to a cloud server via Internet of Things (IoT) applications, utilizing the Wi-Fi communication protocol.

The Internet of Things (IoT) functionality was responsible for the transfer of data from the sensors to the cloud. This process consisted of an Arduino IoT Node MCU microcontroller, RTC DS 1302, and sensors; namely, a DC 200A current sensor, an AC current sensor, a 0–24 V DC voltage sensor, and a 0–225 V AC voltage sensor.

The monitoring application had more dashboards which displayed the data collected from solar panels, battery parameters, PLN panels, and load panels. The data collected were stored in a cloud database, but the research was limited because the data were not used for other functionalities, such as intelligence services, prediction of energy generated by solar panels, or the detection of grid performance failures.

The research did not present clearly if the system could be controlled from a distance, if the data used in Internet communications were encrypted, or if the main principles of cybersecurity were respected over Internet connections. According to paper [28], the inverters from on-grid systems are vulnerable to cyber-attacks: malicious actors can attack photovoltaics by providing false measurements of sensed signals, such as the power generated, or the inverter control system could be sabotaged by the grid current.

Case 6: Khafaga et al. [29] used a predefined dataset for training (20%) and testing (80%) a long short-term memory (LSTM) parameter for a proposed dynamic dipper-throated optimization stochastic fractal search (DDTOSFS) algorithm for photovoltaic systems. The algorithm developed could be used for predicting energy consumption using advanced machine learning concepts. This functionality could be integrated in a monitoring system, because it is important to know how much electrical energy is stored in batteries for stand-alone photovoltaic systems [4] and what could be the financial impact (electricity invoices) for on-grid and hybrid photovoltaic systems.

The dataset could contain wrong values for parameters, and this affects the integrity of the data used during the algorithm training and testing processes. Automatically, the output when the real values of the photovoltaic system's parameters are used will be affected.

Case 7: Aravelo et al. [30] presented a microgrid system which had 15 kW, bi-directional inverters, and was connected to the grid, and for the storage system, Li batteries and supercapacitors (SC) were used. The paper proposed the development of an optimized and efficient failure-detection method by using machine learning and analysis of big data (BD) and a new power smoothing method using SC and batteries for on-grid systems. It was estimated that the system was able to function properly for between 2 and 5 days based on the weather conditions, especially on cloudy days. The proposed method was experimented with in the laboratory under controlled conditions and using PV power fluctuations and failures of photovoltaic strings. In the event of fluctuations exceeding 20% per minute, the batteries enable the supercapacitor (SC) to handle the highest peaks during failure; at this point, the monitoring had a root mean squared error (RMSE) of 0.66–2.47. The smoothing method resulted in a reduction in computational effort: the initial execution time was four times shorter compared to the previous method.

Based on the results obtained in this research, a power smoothing method could be used in energy control in photovoltaic systems. This method could add additional protection to physical photovoltaic systems, mitigating the issues related to the intermittency of power generation. The paper [31] presented the importance of power smoothing and battery behavior and lifecycle in the long term.

Case 8: Kumar [32] proposed the implementation of a microgrid using the photovoltaic systems from four different buildings. There was a 25 kW rooftop solar PV system installed for each building, with Battery Energy Storage System (BESS) parameters of 180 V and 120 Ah for 2 h. The estimated rated load for each building was 20 kW.

The interconnection of the clusters was facilitated by two-stage converters, comprising DC-DC boost converters and bidirectional single-phase voltage source converters (VSCs), which facilitate the distribution of power among the various buildings. Each cluster was equipped with its own BESS, and the four photovoltaic systems exhibited disparate behavior between 12:00 p.m. and 4:00 p.m. The control technique permitted the maintenance of equilibrium in each building integrated in the microgrid through the charging and discharging of the BESSs. Two control signals were employed for the purpose of controlling the system: feedback and feed-forward. The efficacy of the control techniques was validated and tested in a real-time environment using a Real-Time Digital Simulator.

In the solution proposed, the electrical energy could be transferred from one building to another one easily, and in this way, the buildings with little sunlight could benefit from solar energy as much as possible. This research could be implemented easily for daily home-used photovoltaic systems. The research presented an automated control method.

Case 9: Rao et al. [33] used a photovoltaic system with solar panels, sensors, a battery charge module, and a simple monitoring system. The proposed monitoring method could be used for every type of solar system with low costs because it is based on an Arduino microcontroller and few sensors. The monitoring system was able to collect data in real-time from different locations and store them in the cloud.

The data transfer is done using the HTTP protocol, which is not a secure port. For improving the safety of the data and avoiding data breaches, it is recommended to encrypt the data before sending it or storing it on the network or on the cloud [34].

Case 10: Juan M. Cano et al. [35] present a complete and versatile monitoring and control system which can be used in different conditions of PV systems, such as sizing and weather. ZigBee technology was configured, and for remote communications a 3G network was implemented. The proposed implementation used two inverters and both were remotely connected.

The system measured the weather and electrical parameters and sent them to the control unit, which stored them and calculated the control signals. After that, it sent them back to the inverters DC/DC and DC/AC using 3G. The data were visualized and stored in the software named Gambas. It was not mentioned if the data were encrypted or stored in a safe manner, or who had access to the stored data. Additionally, the proposed software solution offered functions such as user authentication and control of the system.

The communication over the Internet used normal protection offered by the IP, TCP/IP, and UDP/IP protocols, but this is not enough, as attackers are knowledgeable about the vulnerabilities given by these Internet protocols [34]. To avoid the attackers' presence, additional safety features should be implemented for data encryption, network traffic over the Internet, and for user authentication in the application.

4.2. Remote-Control Methods for PV Systems

Modern solar systems use modern devices in their implementation and operation which have intelligent functions, such as artificial intelligence algorithms and remote control. Usually, the control system is integrated with a monitoring system, as in [26]. Based on the data collected in real-time by the monitoring system, the control system can quickly detect faults, especially anomalies occurring in the DC and AC outputs [22].

One of the smarter components is the inverter, which can manage the voltage and current during the PV system's operation and can be connected to the Internet by offering remote-control functions, as in Figure 7. For on-grid cases, the voltage, amplitude, and invertor's frequencies are synchronized with each other when the PV system is connected to the grid [36]. Control from a distance can be applied to other components, such as the battery packs, if they have a smart BMS connected, and the charge controller; also, these devices offer functions to modify the PV system's parameters during the solar system's operation: the modification can be done manually by people, or dynamically using AI algorithms which take decisions in real-time based on the data collected in real-time from the PV system [35].

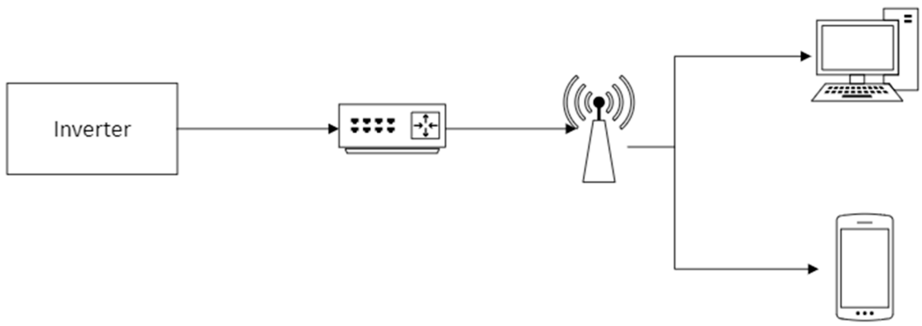

Figure 7. The logical scheme of remote control for an inverter.

This can be done by using transmission protocols such as the Bluetooth, Wi-Fi, ZigBee, and GSM protocols [9]. The PV panels and systems are integrated successfully in IoT applications, from where other IoT components can have a specific behavior or make a decision based on the data collected from the PV panels [24]. The control system requires intervention only in the case of error or anormal behavior, such in [37], where the control function is activated when the temperature value is greater than 40 °C, then the system is cooled; the control function is also activated when the water's temperature is greater than 70 °C, and in this case the hot water is exchanged with cold water. In Table 1 are presented different types of PV systems with control from distance.

Table 1. PV system—remote-control implementations.

Ref.	Communication	Description	Comments
[38]	Wi-Fi	The proposed solution is based on open-access software and cloud services, and the data acquisition function collects data in real-time. The control of system consists in On–Off actions.	The system's remote control is limited to On/Off actions.
[39]	Satellite	A remote performance check including an automated failure-detection routine for PV systems has been developed within the PVSAT-2 project. The solution detects and control remotely the failure of devices such as the inverter, but also failures regarding degradation, module defects, grid outages, power limitations, hot inverter, high temperature, and maximum power point tracking.	The proposed solution was tested, but needs significant improvements to be implemented in real world.

Table 1. *Cont.*

Ref.	Communication	Description	Comments
[11]	Wi-Fi	The LabVIEW software is used to monitor and control. The current, voltage, and temperature values can be controlled.	It is a good and easy solution for systems remote monitoring and control.
[40]	Wi-Fi	A sliding mode control for the DC/DC converter is developed, which ensures the achievement of the maximum power point (MPP) under all environmental conditions. Additionally, a proportional-integral (PI) controller is implemented for the DC/AC converter, which guarantees the power quality. When changes have been implemented, the PV system's signals are measured and remotely managed in order to guarantee the system's continued operation.	The wireless communication allows the operation of the system in real-time, facilitating the detection of faults rapidly and system's robustness.

The automation in solar systems is obtained by the integration of intelligent controllers through the replication of biological intelligence. The intelligent controllers do not require the systems' mathematical modeling and have the ability to approximate non-linearities. There are considered to be three types of intelligent controllers: repetitive controllers (improves the system output waveform), neural network controllers (based on the human nervous system and a connection of many artificial neurons), and fuzzy logic controllers (used to control the system dynamics) [16].

Energy production depends on the environmental irradiance and temperature parameters, which causes PV panels to have nonlinear characteristics. In uniform conditions, there is only one maximum point, called the maximum power point (MPP), which causes a PV system to operate at maximum efficiency. In non-uniform conditions (partial shading effects), multiple MPP are present on the power–voltage correspondence curve due to bypass diodes, which makes the global MPP estimation more difficult [41]. This is the main reason why maximum power point tracking (MPPT) is crucial for PV systems to operate at maximum efficiency. In the literature, more types of MPPT control solutions are proposed to improve systems' efficiency [42], and the MPPT techniques are classified into four main categories, as presented in [43]:

- Classical MPPT control techniques
- Intelligent MPPT control techniques
- Optimization techniques
- Hybrid techniques

Every category contains subcategories, which are presented in [43]. It is important that the proper MPPT technique is chosen when harvesting the peak power from a PV system. Table 2 briefly describes various MPPT techniques.

Table 2. MPPT control methods.

Reference	MPPT Method	Description
[44]	Adaptive Neuro-Fuzzy Inference System (ANFIS)	The ANFIS MPPT technique was leveraged in this investigation. The findings demonstrated that the maximum power point (MPP) could be successfully tracked in partial shading conditions.
[45]	Artificial Neural Network (ANN)	A novel method for tracking MPPT was proposed. It was concluded that the proposed method could easily track the MPPT.
[46]	Hill Climbing Adaptive Neuro Fuzzy Inference System (HC-ANFIS)	The solution proposed shows that the irradiance and temperature values could be collected in real-time and the maximum voltage predicted

Table 2. *Cont.*

Reference	MPPT Method	Description
[47]	Perturb and Observe (P&O)	The proposed algorithm is based on the utilization of voltage sensors. The results of the simulation and experimental studies demonstrated that the proposed method was effective in enhancing the dynamic performance of the PV system.
[48]	Fuzzy particle swarm optimization (FPSO)	A hybrid FPSO was designed with the objective of achieving frequency stabilization under a range of loading conditions. It was determined that the frequency stability was enhanced when the fuzzy logic controller (FLC) method was employed in conjunction with the hybrid FPSO.
[49]	Improved Perturb and Observe (IP&O)	An enhanced P&O MPPT algorithm was modelled using MATLAB/SIM-ULINK software. The efficiency obtained in the tests was 99.7%.
[50]	Cuckoo Search (CS)	The research compared the particle swarm optimization (PSO), incremental conductance (INC), and CS methods. Under shading conditions, CS has better results than PSO.
[51]	Constant voltage (CV)	The algorithm designed automatically modifies the reference voltage, taking into consideration the changing meteorological conditions.

5. Artificial Intelligence

Artificial intelligence (AI) algorithms are known for their ability to simulate human intelligence and problem-solving capabilities. The AI models learn from examples, are able to work with incomplete data, and, once trained, can perform prediction at high speeds. The machine learning algorithms are classified into three categories [52]: supervised learning, unsupervised learning, and reinforcement learning. The neural network (NN) learning algorithms are part of the deep learning category, and they were the most used learning algorithms in several literary works [53]. Their working mode is as follows: nodes in one layer are connected to nodes in the next layer. Neural networks have three types of layers: input layers, hidden layers, and output layers, as presented in Figure 8 [54]. The number of hidden layers may vary.

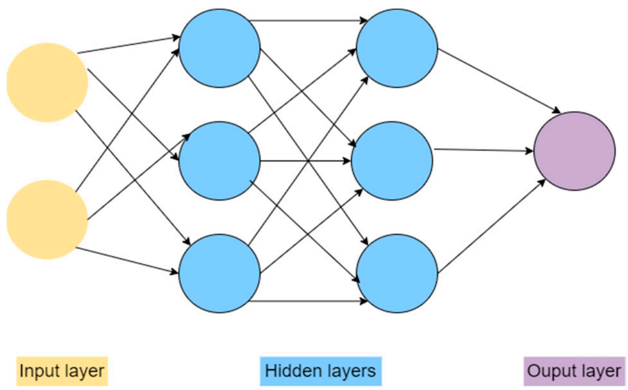

Figure 8. Layers of a neuronal network.

The next rule should be respected to ensure a neural network is properly trained and tested: the number of outputs of a layer should be equal with the number of inputs of the next layer. An activation function could be implemented as in [55] where was used ReLU activation function to easily train the model and obtained the desired performances and results.

The following are some AI techniques which can be used in the photovoltaics technology:

- Artificial Neural Network (ANN)
- Support vector-machine (SVM)/Support vector-regression (SVR)

- Generic Algorithm (GA)
- Bootstrap Aggregated Neural Networks (BANN)
- Back-propagation neural network (BPNN)
- Adaptive Neuro-Fuzzy Inference System (ANFIS)
- Naïve Bayes (NB)
- Historical Similar Mining (HISIMI)
- Transient System Simulation Tool (TRNSYS)

The advent of intelligent and smart PV systems, especially those based on AI, has led to a growing popularity of PV systems for energy production and consumption. This is due to their ability to handle new opportunities and issues in photovoltaics, such as power management [56]. Various studies have been published recently that highlight the importance of AI techniques in this field. These include prediction of solar radiation, prediction of energy production, solar energy modelling, sizing of photovoltaic systems, and electrical load prediction [57].

5.1. Artificial Intelligence Algorithms Integrated in PV Systems

The photovoltaic industry is witnessing a notable advancement in the sophistication, durability, and responsiveness of its products. This is largely attributed to the integration of sophisticated systems, such as AI-based approaches and the Internet of Things (IoT). Artificial intelligence (AI) techniques have a significant impact on sustainable renewable energy, enhancing system productivity, reducing costs, and addressing complex challenges.

In modern solar systems, AI algorithms are implemented to estimate daily/monthly global solar radiation from sunshine duration [58]; predict meteorological data, including solar radiance, ambient temperature, humidity, wind speed, and sunshine duration [58]; size the parameters of the PV system [59]; manage the PV system [58]; and detect broken system components [60].

Smart grid systems can handle all tasks autonomously (tracking the MPP, handling the faults, and maintaining the stability) using machine learning and deep learning approaches [61]. AI algorithms are integrated with IoT functionality, and they are part of the PV monitoring and control systems, as presented in Case 6 and Case 7.

The input data for AI algorithms have different forms, such as in [27,28], based on the format of the collected data from different devices. Additionally, the inputs of AI models can be represented by images. Shaban [60] proposed a fault detection and classification system for PV systems based on electroluminescence images.

A review of the literature reveals that there has been a growing implementation and analysis of AI-based models in the field of solar power system modelling, optimization, and sizing and the resolution of data issues [62]. In the past, the implementation of system optimization and the design of cells were based on theoretical models and empirical approaches. In the present era, engineers and researchers have devised novel procedures and contemporary solutions by leveraging the capabilities of AI to enhance the affordability, functionality, and efficacy of PV technology [63]. The literature on the implementation of AI techniques in PV systems indicates a shift in the standard approach to the future development of solar energy and PV applications, as illustrated in Table 3.

Table 3. AI methods integrated in PV systems.

Ref.	AI Model	Solar Energy Applications	Discussions and Results
[64]	ANN	PV panel power prediction	The optimal configuration was identified, and the results demonstrated the efficacy of the proposed methodology for short-range power applications.
[65]	SVR, BPNN	PV panel energy prediction	In comparison to the traditional ANN model, the SVR and BPNN models demonstrate enhanced prediction accuracy and reduced computational complexity.

Table 3. *Cont.*

Ref.	AI Model	Solar Energy Applications	Discussions and Results
[66]	ISCE (improved shuffled complex evolution)	Parameter extraction of solar cell models	It is perceived as an accurate and effective method for addressing the factor extraction challenge inherent to solar cell models.
[67]	ANFIS	Hourly worldwide, radiation prediction	The ANFIS model demonstrates superior performance in replicating the system output compared to traditional arithmetic models.
[68]	ML, SVR	Global solar radiation prediction	The experimental results demonstrate a satisfactory estimation for Egypt and provide evidence of the effectiveness of support vector regression (SVR) models.
[69]	GA	Forecasting of solar power	It was observed that there were significant fluctuations in the results obtained in terms of authentic power output, with considerable variation occurring within a single hour.
[70]	GA-BPNN	Prediction of mean temperature	The most optimal outcomes were observed when BPNN and GA-BPNN were integrated. This approach may facilitate the development of expedient and pragmatic models for forecasting outdoor heat environments.
[71]	GA	Maximum power point tracking (MPPT) solar tracking	The device is employed for the purposes of tracking and control. A microcontroller was designed to facilitate the implementation of the GA tracking technique. It was observed that the system's implementation was effective.
[72]	BPNN	Diffuse solar radiation prediction	The BPNN technique employs a set of characteristics that facilitate the generation of precise evaluation indices. These include data pertaining to the month of the year, mean temperature, daily duration, wind speed, humidity (relative), rainfall, and daily worldwide.
[73]	ANN and TRNSYS	Prediction of performance of industrial control systems (ICS)	It has the potential to supplant the necessity for such tests entirely. The system allows for the simulation of individual components and the generation of reports based on the configured parameters.

The efficiency of PV panels represents a crucial domain where artificial intelligence (AI) can significantly contribute to optimizing the system's operational mode. The application of AI algorithms and advanced data analytics methods has resulted in more precise measurements and evaluations of the system's parameters, which affect the efficiency of solar panels (temperature, intensity of incident light, and shading effects) [74]. In order to achieve an increase in energy production, AI algorithms are designed to have the capacity to dynamically modify the operating parameters and working conditions of solar panels by means of continuous observation and evaluation of the operating conditions in real-time. Based on real-time measurements and evaluations, the AI algorithms are capable of rapid adaptation. The optimization of operating conditions through the application of AI has resulted in enhanced overall system performance, stability, and efficiency.

The generation of solar energy is contingent upon meteorological conditions [75]. A review of the literature reveals that AI-based algorithms, techniques, and approaches are compatible with historical and meteorological data for solar energy generation. These factors contribute to the stability of systems and enhance energy production.

5.2. Advantages and Disadvantages of AI for PV Systems

The capacity of AI systems to anticipate energy production and consumption outcomes enables the implementation of optimization strategies and the attainment of enhanced efficiency. The utilization of machine learning algorithms to analyze historical data and weather patterns facilitates the forecasting of energy output and the subsequent adjustment of system settings in accordance with this analysis. By monitoring and reacting to changes in energy demand in real-time, AI-controlled PV systems ensure the efficient and cost-effective utilization of energy [76].

While AI can be beneficial for PV systems, it is important to consider the potential drawbacks, as outlined in Table 4. For example, generation discontinuity is caused by seasonal fluctuations. There are challenges and open issues pertaining to the application of artificial intelligence (AI) approaches in renewable energy systems, including photovoltaics [77]. The following areas require further investigation:

- data acquisition and auditing
- energy storage and grid integration issues
- performance and explain ability issues
- safety and protection against data breaches
- stability and generation in predictive modeling
- modeling of various faults simultaneously

Table 4. AI methods—advantages and disadvantages.

Ref.	AI Model	Advantages	Disadvantages
[64]	ANN	The model is advantageous due to its simple architecture and these algorithms play an important role for remote management of PV systems.	The AI model requires long training time, which is the limiting factor.
[65]	SVR, BPNN	Accurate forecasting with less computational modeling compering with other models.	Average forecasting errors.
[66]	ISCE	It gave a sound solution to the parametric extraction issue and the ISCE algorithm obtained the best results for parameters extraction from PV cells and panels.	N/A
[67]	ANFIS	It gives accurate and feasible predictions.	The algorithm's performance is dependent in the quality of input data.
[68]	ML, SVR	Good estimation and accuracy.	Errors in the training and testing datasets.
[69]	GA	Ability to source the spot standards for power prediction.	Complexity of the system and computational resources required for the algorithm to provide accurate forecasting.
[70]	GA-BPNN	This approach can lead to the prediction of outdoor mean temperature using reduced computational resources.	Preparation of datasets used for training and testing could be difficult.
[71]	GA	The primary advantage is that a non-conventional approach was successfully simulated to provide solar tracking under the same atmospheric changes.	The extraction of the maximum power of the PV panel when the PV panels are partly shaded.
[72]	BPNN	The algorithm has accuracy and it is cost-effective.	The estimation of error in the input variables.
[73]	ANN and TRNSYS	Few rare situations can be created for testing and evaluating the prediction of ICS performance.	From a financial point of view, the software is expensive.

6. Cybersecurity

The expansion of photovoltaic systems within the energy sector is driven by three key factors: technological advancements, cost-effectiveness, and environmental concerns. Two-way communication technology and computational intelligence are employed by smart PV systems to facilitate the integration of the entire energy system, encompassing the full range of generation and consumption endpoints. Despite the multitude of advantages, this approach renders photovoltaic systems susceptible to security threats, thereby providing hackers with novel avenues for exploitation of vulnerabilities. The expansion and complexity of photovoltaic systems may render them susceptible to cyber threats, which could potentially disrupt operations and impact energy infrastructure. Various components of photovoltaic systems (advanced meters, inverters, sensors, etc.) represent additional vulnerabilities and risks, opening to hackers a door for taking advantage of vulnerabilities in photovoltaic systems. It is necessary to implement robust measurements (intrusion detection, secure ports/protocols, and continuous tracking solutions) to safeguard systems against advanced cyber risks. In the last several years, more intelligence algorithms using AI techniques were developed for detecting cyber-attacks for photovoltaic systems [77].

6.1. Vulnerabilities and Threats for Photovoltaic Systems

Photovoltaic system vulnerabilities are represented by insecure communication protocols, lack of access control, lack of parameter sanitization, backdoor and hard-coded accounts, and cross-site scripting [78]. The most popular types of cyber-attacks for photovoltaic systems are as follows:

a. False data injection—once the intruders can change and manipulate the data collected from sensors, a cyber-attack named false data injection can be easily planned [79].
b. Man-in-the-middle (MITM)—an intrusive party embeds itself within a conversation between two communication devices with the intention of eavesdropping on either one of the devices. This is achieved by making it appear to be a normal exchange of information [80].
c. Denial of service (DoS)—the primary targets for this type of attack are the protocols, with the intention of overloading the communication channels [81].
d. Replay—those engaged in malicious activities capture network traffic and act as the primary source by forwarding the traffic to the intended recipient. The attacker creates delays in data transfer or the data are resubmitted [82].
e. Brute force attack—the objective of the attacker is to gain unauthorized access to the system by attempting to guess the usernames, passwords, or encryption keys on multiple occasions. In the event that malevolent actors have gained access to the system, they may remain undetected for an extended period, provided that they are able to masquerade as a legitimate user. Concurrently, they may establish clandestine access points, navigate the system undetected, comprehend its functionality and objectives, and procure confidential data. In addition, they are capable of configuring and executing malicious scripts [83].

Three major security factors are commonly viewed as risks [84]:

- the attackers and the vulnerabilities in the system
- the produced impact
- the repercussions of the attack

A total of 23 known vulnerabilities in PV systems were analyzed in the study [85], their root causes were investigated, and mitigation strategies were proposed. A vulnerability database [86] was used to determine the vulnerabilities.

6.2. Cyber-Security Preventive and Detection Measurements for PV Systems

For better digital protection for solar panels, preventive or detection measurements can be implemented [78]: data encryption, implementation of firewall and proxy rules, implementation of the least-privilege principle, configuration of antivirus software, implementation of two/multi-factor authentication, implementation of microsegmentation, encrypted traffic, and the usage of secured protocols such as HTTPS, TLS, SSH, etc. Incident response and regular security updates play an important role in keeping a PV system secured. It is important that industry stakeholders, academics, and policymakers work together to establish best practices and improve PV systems' security.

Table 5 shows the threats which could appear during the operation of PV systems, and countermeasures to improve their security.

There could be implemented an intrusion detection system (IDS) which monitors a system's behavior and reports security violations. In contrast to the IDS, an intrusion prevention system (IPS) blocks a detected network connection by closing the port or dropping the packets. IDSs and IPSs are indispensable in system monitoring [87]. The alerts generated by IDSs and IPSs are visible in SIEM tools. AI algorithms have the role of detecting the malicious traffic and protecting the system by taking the proper action based on the events that occurred in a specific timeframe. In research [87], an AI-SIEM solution was presented which can detect malicious activity and take preventive actions. The solution proposed had a dashboard for security operation center (SOC) analysts (people who investigate alerts and make the proper decisions for difficult cases where the AI algorithms fail).

Table 5. Cybersecurity threats and countermeasures for PV systems.

References	Threats	Prevention/Detection Measures
[85]	False data injection attack	Neural network-based attack detection Use of intrusion detection system Add intrusion signatures Add proxy and firewall rules Access parameter sanitization
[88]		Encryption mechanism: Transport Layer Security (TLS) protocol
[89]	Denial of service attack	Firewall rules Antivirus solution installed
[90]		Encryption implementation
[91]		Prediction framework: cellular computational network (CCN)
[92]		IDS
[80]	Man-in-the-middle attack	Communication protocol encryption Network security (microsegmentation, firewall, proxy, load balancer rules)
[93]		Data encryption
[94]		Encryption and checksum implementation
[95]		Transport Layer Security (TLS) protocol
[92]		SSH public key authentication
[93]	Relay attack	Use of secured protocol (sTELNET instead of TELNET protocol, or FTP-SSL for file transfer instead of DTP)
[93]	Password attack	Implementation of least privilege principle Implementation of MFA (Multi-factor authentication)
[96]		Strong password Role-based access

6.3. Cyber-Attacks on Power Energy

A discussion of major cyber-attacks affecting the PV systems and energy industry in the last few years is presented here.

One of the most elaborate and cleverly executed cyber-attacks on a power grid occurred in Ukraine on 23 December 2015. It caused a six-hour outage for hundreds of thousands of consumers in and around Kiev [97]. A regional distributor was affected, and there have been reports of malware found in Ukrainian companies across a range of critical infrastructure. This is believed to be the first case to have a significant impact on the security and safety of the power grid everywhere. The investigation report [98] showed that the intruders used remote industrial control system (ICS) client software or pre-existing operating system remote administration tools over virtual private network (VPN) connections to perform malicious remote actions on the circuit breakers. To facilitate remote administration, the attackers are believed to have obtained legitimate access and credentials (usernames and passwords) in advance.

A second cyber-attack took place in Ukraine on 17 December 2016, almost a year after the previous attack. It affected the Pivnichna substation outside Kiev, leaving people without electricity [99]. It caused a blackout that lasted for an hour, and a fifth of Kiev's electricity consumption was lost. The analysis report [100] shows that the malware called "CRASHOVERRIDE" was used in the second attack from Ukraine. Its frameworks include modules specific to ICS protocol stacks, but it also includes non-ICS-specific modules such as a wiper (deletes files and processes from the running system to launch a destructive attack on operational technology equipment).

On 5 March 2019, attackers targeted a renewable energy company based in the US. The company experienced a denial-of-service attack and the event caused grid operators to lose communication with solar and wind generation sites, leaving operators without access to the generation systems for around twelve hours [101]. A German wind turbine operator was affected by a cyber-attack in February 2022. It was reported that the remote monitoring and control of thousands of wind turbines had failed due to a communication failure between a satellite and the wind turbines [102]. On 12 April 2022, the Computer Emergency Response Team of Ukraine (CERT-AU) reported a cyber-attack on a Ukrainian energy company [103]. The attackers used a malicious program named Industroyer2 (a version of CRASHOVERRIDE used in 2016) to target elements of critical infrastructure, such as high-voltage substations. The attack was known and mitigated before it caused greater harm, otherwise two million people would have been affected by the blackout [104]. On 26 October 2022, attackers targeted one of Germany's largest municipal utilities. The IT disruption affected the availability of customer services. The critical infrastructure of the facilities was not affected due to a rapid response that prevented greater damage [105]. On 18 August 2023, an Australian software developer for energy companies was the target of a data breach cyber-attack [106]. The personal data of employees may have been intercepted by an external actor. The incident affected the company's systems in Australia and the UK. In response to the incident, the company disabled some links between its corporate and customer-facing systems. It is not known how the event occurred or who these intruders were [107].

7. Discussion

Firstly, this article describes and compares 10 theoretical and experimental approaches to determine the right configuration of photovoltaic systems. Each approach takes into consideration one aspect of the photovoltaic systems, but photovoltaic systems' complexity is increasing significantly and they are more exposed to risks and threats. These cases were chosen because each of them addresses different and novel aspects of a photovoltaic system. The scope of this section is to show the complexity of modern photovoltaic systems and how to design and implement them properly by using the latest technology trends. Most of the photovoltaic systems are used for individual needs and it is hard to choose the right configuration, as it is needed to take into consideration many aspects, such as the system type, its configuration, physical and digital security, and how the system can be remotely monitored and controlled. Most of the existing photovoltaic systems meet their users' daily and monthly needs for power generation and consumption, but people are interested in advanced functions, such as remote access, prediction of power generation in specific situations, and the system's security. All these aspects make photovoltaic systems more complex and expose them to physical and digital risks (Table 6).

The security of photovoltaic systems is represented by two parts: physical and digital. The monitoring and control systems are important components for the physical safety of the photovoltaic system. In a stand-alone photovoltaic system, the system's signals are tracked to avoid the system overloading or overcharging. For example, for battery packs, limits are set to avoid overcharging and overloading and to maintain their normal behavior as much as possible. If the batteries' parameters are outside of the set limits, the batteries represent a high risk of fire for the photovoltaic system and for the owners of the system.

The temperature influences the physical security of the photovoltaic system. A high value of temperature changes the system's mode of operation. When the temperature exceeds a predefined value, a special function can be configured to start a cooling fan for batteries, cleaning system for solar panel cooling, etc. There are smart applications which are used for monitoring and control operations. These applications act immediately based on data collected in real-time. If the application has included machine learning functions, then control decisions could be taken fast based on the past behaviors in the same or similar conditions.

Table 6. Use-case implementations.

Ref.	Type of PV System	Remote Control	AI Techniques	Cybersecurity Measures
[21]	stand-alone	x		
[22]	on-grid		x	
[24]	stand-alone		x	
[26]	stand-alone, on-grid, hybrid			
[27]	Hybrid			low
[29]	stand-alone, on-grid, hybrid		x	
[30]	on-grid, hybrid		x	
[32]	stand-alone	x		
[33]	stand-alone	x		low
[35]	stand-alone, on-grid, hybrid	x		low

The presented cases in Section 4 are exposed to cyber-attacks due to the devices used and the monitoring and remote-control systems used in each photovoltaic system's implementation. They have access to the Internet and open a door for hackers. Almost all the discussed systems do not present security features and an attacker has the opportunity to be easily present in the photovoltaic system. If attackers are present, they can configure devices and device parameters, manipulate data, and manage the PV system's behavior, and their presence is unknown to the person who owns the system. To avoid such situations, strong security is needed: a complex authentication method should be configured for users (MFA: something you know, something you have, and something you are), secured ports and protocols should be used, the network traffic should be encrypted, and the firewall and proxy rules should be configured accordingly based on the networks the system is a part of.

Taking into consideration the above discussions, photovoltaic systems should accomplish many criteria, and the perfect system's configuration is hard to be made and should be a perfect combination of the discussed cases in the above sections. In Case 1, the PV system implementation is suitable for any weather conditions because the electricity is available all day due to the hybrid PV system implementation. In Case 2, the monitoring algorithms could be used for detecting faults of PV systems for home use, especially anomalies occurring in the DC and AC outputs. The algorithms should be improved with modern techniques such as deep learning-driven models. In Case 3, the proposed implementation had a good monitoring system using IoT applications, remote access, detection and classification of faults, and power prediction. Case 4 presented a monitoring solution which is easier to implement, and the risk of device breakdown was smallest because the PV system proposed contained fewer electronic devices. A similar approach was presented in Case 9, but the monitoring system used another solution for transferring the data from the PV system to the cloud. The data transfer was not safe, as in Case 10, where the normal security offered by the IP, TCP/IP, and UDP/IP protocols was used. Additionally, Case 10 proposed a control system which plays an essential role during the PV system's operation mode. Case 5 presented a complex PV system implementation and monitoring which is fit for home use. In reality, people use a similar approach due to the PV system's implementation and remote monitoring system functions. The prediction function from Case 6 could be integrated easily in the monitoring system from Case 5. The smoothing method presented in Case 7 could be integrated into the PV systems presented in Case 1 and Case 5, where it could add better energy control and additional protection to the physical PV system, mitigating the intermittency of power generation.

More individual PV systems for home use could be connected into a micro-grid, as presented in Case 8, but it is very important how they are monitored and controlled from a distance. The main advantage was that a building with more sunlight could share its produced energy with other buildings which generated less energy due to shadowing conditions. A good photovoltaic system which could be integrated and operating in normal parameters in any location and meteorological conditions should contain the following aspects:

- The system implementation as in Case 1.
- A monitoring solution for detecting faults and anomalies of PV system, as in Case 2, and notifying the user when an unplanned event occurs.
- A simple remote-monitoring solution which collects data in real-time (Case 9), and the user can easily access the collected data from PV system, as in Case 5. In addition, the supervision application should have functionalities to predict energy consumption, as in Case 6.
- A good control system for energy storage (Case 8) and consumption (Case 7) which could take predefined actions in specific situations, especially in risky cases which potential damages.
- Physical (Case 1) and digital security: similar to Case 9, which should be made better by using the HTTPS protocol, but also Case 10 proposed data transfer with the minimal security offered by Internet protocols.

AI plays a crucial role in finding the right size of a PV system and tracking the values of parameters. AI techniques are able to quickly make decisions and dynamically adjust a solar system's parameters based on collected data in real-time and assure the system's operation in safe conditions. Another important aspect is that they could offer a good optimization of parameters during the solar system's operation based on real-time data collection or based on historical data, thus avoiding overloading or energy losses.

8. Conclusions

The objective of this review is to provide a comprehensive and unified source of information for scientists, engineers, and researchers engaged in the investigation of recent advancements and challenges associated with the implementation and control of PV systems. These systems employ cutting-edge techniques from artificial intelligence and cybersecurity domains. The role of the remote control of PV systems and the use of AI and cybersecurity techniques for PV systems was subjected to a comprehensive evaluation. A review of remote-control, AI algorithm, and cybersecurity techniques has been conducted, with particular attention paid to their potential benefits. The remote control of PV systems necessitates the capacity to rapidly respond to alterations in the system's operational status, which can be achieved through the utilization of artificial intelligence algorithms. Artificial intelligence approaches can effectively supplant traditional physical modelling methods, as they necessitate fewer computational resources and are not dependent on sophisticated knowledge of internal system parameters. Such techniques have been successfully applied in numerous PV-related contexts. Conversely, the deployment of remote-control techniques and AI solutions may potentially increase the risk of cyber-attacks. The potential for cyber-attacks on PV systems is significant. These attacks may include false data injection, replay, denial of service, and brute force credential attacks. Such attacks could affect the PV system's operational mode by exploiting vulnerabilities. These include the use of insecure communication protocols, a lack or poor encryption techniques, a lack of access control, and a lack of parameter sanitization. The integration of innovative hybrid remote-control, AI, and cybersecurity techniques will foster greater confidence in the reliability of PV technology. This research is limited to PV systems which are designed to use monitoring and control methods combined with AI and cybersecurity approaches. Based on this analysis, future work will focus on implementing a stand-alone PV system that can be remotely controlled using AI and cybersecurity best practices. A new mobile application will be developed to cover the issues found, with a user-friendly interface which will offer important information about our PV system and its working mode by using AI technology. The cybersecurity measures will be implemented to ensure safe communication between the PV system and the mobile application.

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