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Harnessing the Cloud: A Novel Approach to Smart Solar Plant Monitoring

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Abstract: Renewable Energy Sources (RESs) such as hydro, wind, and solar are merging as preferred alternatives to fossil fuels. Among these RESs, solar energy is the most ideal solution; it is gaining extensive interest around the globe. However, due to solar energy's intermittent nature and sensitivity to environmental parameters (e.g., irradiance, dust, temperature, aging and humidity), real-time solar plant monitoring is imperative. This paper's contribution is to compare and analyze current IoT trends and propose future research directions. As a result, this will be instrumental in the development of low-cost, real-time, scalable, reliable, and power-optimized solar plant monitoring systems. In this work, a comparative analysis has been performed on proposed solutions using the existing literature. This comparative analysis has been conducted considering five aspects: computer boards, sensors, communication, servers, and architectural paradigms. IoT architectural paradigms employed have been summarized and discussed with respect to communication, application layers, and storage capabilities. To facilitate enhanced IoT-based solar monitoring, an edge computing paradigm has been proposed. Suggestions are presented for the fabrication of edge devices and nodes using optimum compute boards, sensors, and communication modules. Different cloud platforms have been explored, and it was concluded that the public cloud platform Amazon Web Services is the ideal solution. Artificial intelligence-based techniques, methods, and outcomes are presented, which can help in the monitoring, analysis, and management of solar PV systems. As an outcome, this paper can be used to help researchers and academics develop low-cost, real-time, effective, scalable, and reliable solar monitoring systems.

Keywords: solar plant monitoring; industrial internet of things; IoT systems; cyber-physical systems; cloud-based architecture; decentralized architecture; cloud continuum; edge computing

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1. Introduction

With an increasing world population, world energy demand is growing exponentially. It is estimated that the world's total energy demand will increase to 30 TW by 2050 [1]. Currently, more than 65% of world energy demand is fulfilled by carbon-intensive fossil fuels such as oil, gas, and coal [2]. Major challenges associated with fossil fuel-based power generation range from greenhouse gas (GHG) emissions, climate change, depleting resources, price volatility, security, and dependence on imports from a limited number of countries having adequate fossil fuel supplies. To overcome these challenges, renewable energy sources (RESs) such as solar, wind, hydro, and biomass are emerging as optimum solutions for sustainable energy generation. According to an International Energy Agency (IEA) report, 28% of the world's energy demand will be met by renewable sources by 2021 [3]. Among RESs, solar energy has emerged as the cleanest, cost-effective, efficient, and reliable solution. Moreover, its most prominent feature is its ubiquitous presence and sharply falling costs with technological advancements. In 90 min, enough sunlight strikes the earth's surface to provide the entire world's energy demand for one whole year. Over the last decade, equipment cost has dropped 60% from USD 2/watt to USD 0.2/watt [4]. Solar energy can play a vital role in filling electricity demand gaps without having the danger of GHG emissions.

With the exponential increase in installed solar capacity, the need for more accurate, low-cost monitoring and performance prediction systems has become imperative. With advancements in technology, IoT (Internet of Things)-based solar plant monitoring systems are increasingly becoming viable [5]. Such IoT-based systems are instrumental in optimizing solar plants' performance through predictive diagnosis and performance evaluation, thus mitigating unwanted power disruptions. Salient features for employing such systems are mentioned as:

1. Monitoring of solar plants installed in remote and hard-to-reach areas. Manual monitoring of solar plants in such areas is expensive, both in terms of cost and manpower needed.
2. A solar plant's performance is highly dependent on meteorological parameters (such as solar irradiance, ambient temperature, sunlight spectrum, and dust particles), resulting in unexpected power fluctuations [6,7].
3. In [8], it has been reported that about 14% of solar panels develop a major fault within a year of operations. Therefore, panel-level monitoring in real time can help in undertaking in-time diagnostics, evaluation, and performance enhancement strategies [9,10].
4. Panel-level monitoring can be instrumental in assessing efficiency, productivity, and profitability of solar installation as a whole. This can also help in the timely replacement of under-performing modules to keep the energy output and profit margins above a threshold. For example, as reported in [10], an investment of only USD 30 in an IoT-based monitoring system for a 4 KW solar plant for timely solar panel cleaning resulted in a return of USD 1200 per year.

A typical IoT-based solar monitoring system comprises numerous interacting, geographically spread nodes that sense operational (meteorological and electro-physical) parameters of a solar plant. These sensed data are then transmitted wirelessly to servers (located locally or on a cloud platform) either periodically or upon the occurrence of a certain event, allowing stockholders to perform predictive diagnostics and efficient management of solar plants. It is therefore imperative to devise and formulate cost-efficient, reliable, and scalable IoT architectural paradigms.

In this paper, we present a review and comparative analysis of different IoT architectural paradigms which are employed for solar plant monitoring in the existing literature. Underlying technologies such as compute boards, sensors, communication, and cloud platforms employed have been analyzed. Two commonly employed IoT architectures (centralized and distributed computing) are explored and their associated challenges are presented in detail. This work highlights the shortcomings of current approaches and provides guidelines for further efficiency enhancements. This enhancement is proposed through the recommendation of employing an edge computing paradigm that is implemented through commonly used, readily available, cheaper, and open-source hardware and software. The proposed solution is IEC61724 standard-compliant with the ability to monitor performance, fault detection, and reporting at the module level. This solution is suitable for both small- and large-scale solar plant monitoring, with the added advantages of low cost, reliability, scalability, and security. The overall architecture of this review paper is based on comparative analysis and proposed methods in the literature, IoT architectural paradigms, primary technologies, active architectures, and AI-based techniques, as shown in Figure 1.

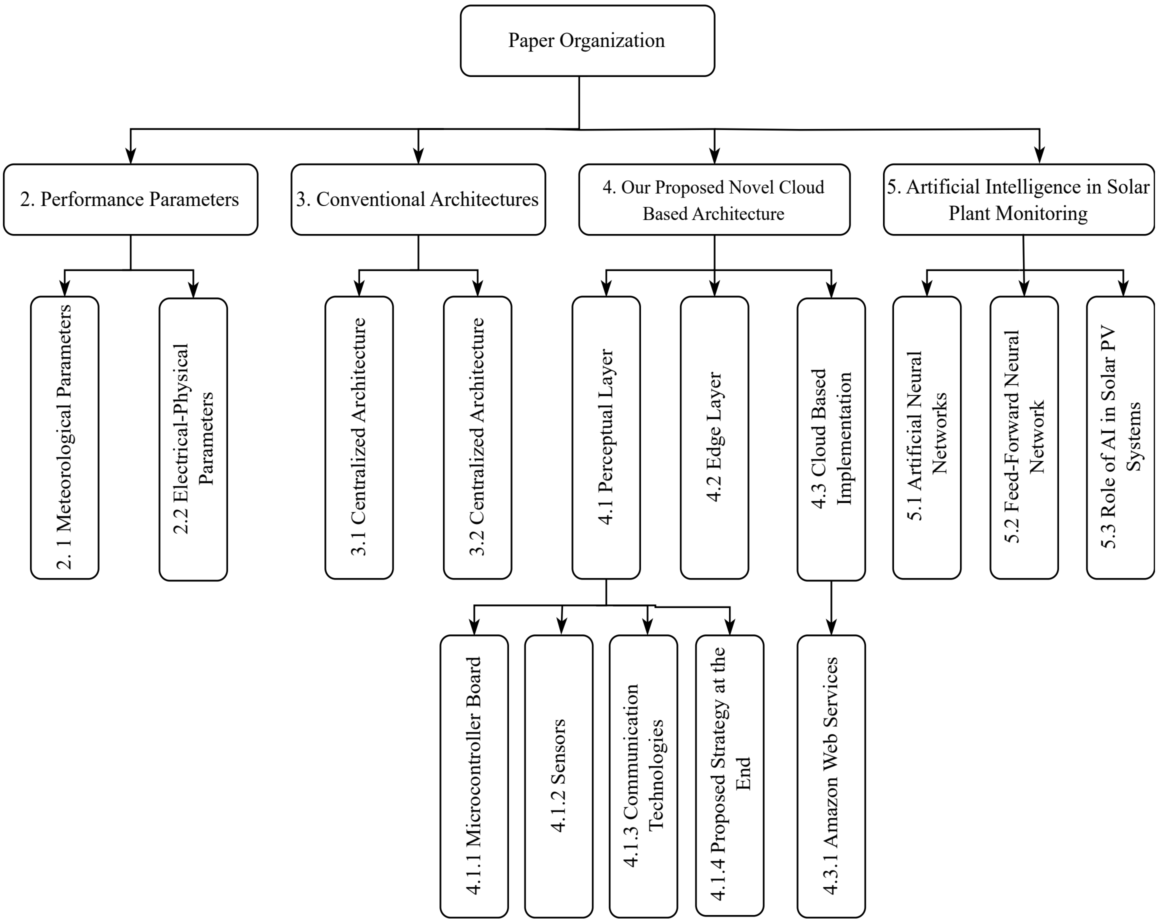

Figure 1. This figure shows the overall overview of the paper. This paper spans a comparative analysis of the proposed methods in the literature, IoT architectural paradigms, primary technologies, our novel cloud-based system, and a discussion on AI-based techniques.

The rest of the paper is organized as follows. Section 2 details performance parameters affecting solar plant efficiency. In Section 3, the related literature has been explored. Section 4 presents a novel cloud-based architecture, leveraged by the introduction of an edge computing paradigm, with recommendations on the most ideal practices (hardware, software, and communication technologies) for the deployment of a smart solar plant. In Section 5, we presented different approaches and techniques for monitoring, analysis, and management of solar PV systems from the perspective of artificial intelligence (AI). Section 7 draws the conclusions.

2. Performance Parameters

Increasing solar plant efficiency through monitoring has been a challenge and is under the intense scrutiny of researchers. Factors affecting a solar plant's efficiency can be broadly characterized as either meteorological or electro-physical parameters [11], as presented in Table 1. For accurate performance evaluation, it is imperative to monitor these parameters at both panel and system levels [12]. These sensed parameters need to be analyzed and correlated for predictive diagnostics at each solar module level [4,12–14]. The overall output of any given solar plant is proportionally dependent on each individual solar panel's output. In this context, the IEC61724 "Photovoltaic System Performance Monitoring" standard has been devised for solar plant performance evaluations [15,16]. The standard classifies solar plant monitoring systems into three classes, as listed in the details below [15]:

- Class A demands for higher accuracy and precision and is devised for utility-scale solar plants. The sampling rate interval is set to 1 min frequency. The accuracy of sensed electrical parameters should be better than 2% of the reading. Ambient temperature readings should be within ±2 °C of actual ambient temperature. Variance in sensed irradiance should not be greater than 8% (ranging from 100 W/m^2 to 1500 W/m^2) [15]. The uncertainty in wind speed should be 0.5 m/s for wind speeds less than 5 m/s and it should be less than 10% for speeds greater than 5 m/s [16].
- Class B systems have medium accuracy and precision. Class B is implemented in large commercial solar plant systems. The required sampling interval is 1 min, with the recording interval set at 15 min [15].
- Class C systems have basic accuracy and precision is mainly used in smaller commercial and residential installations. In this class, the maximum recording interval can be 60 min with a sampling interval of 1 min [15].

A timestamp is associated with each sampling record and is synchronized using GPS or network time protocol (NTP)-based time. Communication technology employed should be able to transmit sensed data anywhere irrespective of the solar plant's installed location, with transmission delivery speed in accordance with the sampling interval. For the aforementioned reasons, wireless technologies are preferred for decentralized systems [17].

Table 1. Meteorological and electro-physical parameters affecting solar plant's energy output.

Meteorological Parameters	**Electrical Parameters**
Total irradiance (G_i), Ambient temperature (T_{amb}), Module temperature (T_{mod}), Wind speed (WS), Wind direction (WD), Humidity (H), Barometric pressure (x), Dust (D), Light Intensity (LI), Rain (R), UV radiations (Uv), Angle of Tilt (A_T)	**1. Photovoltaic Array:** Output Voltage (V_A), Output Current (I_A), Output Power (P_A), Output Energy (E), Duty Cycle (DC)
	2.Utility Grid: Grid Voltage (V_U), Current to Utility Grid (I_{TU}), Power to Utility Grid (P_{TU}), Power from Utility Grid (P_{FU}), Utility Grid Impedance (Z)
	3. Load: Load Voltage (V_L), Load Current (I_L), Load Power (P_L)
	4. Battery: Battery State (B_S), Battery Current (I_B), Battery Voltage (V_B), Battery Temperature (T_B)
	5. Controller: Controller Current (I_C), Controller Voltage (V_C), Controller Temperature (T_C)

2.1. Meteorological Parameters

Meteorological parameters (such as solar irradiance, ambient and panel temperature, soiling, humidity, clouds, wind, rain, and dust) play an oversized role in each module's energy output [18]. Statistics from "World Energy Data" explain that energy consumption with renewable energy resources reaches 23.6% of world energy consumption [19]. Installation configuration of solar panels (such as PV array size, module configuration, and panel orientation in reference to sun direction) also affects each module's energy output [20,21]. Solar arrays are installed facing south at a certain angle to capture optimum solar irradiance. Depending upon solar installation configuration, varying meteorological parameters can affect the overall output of a solar plant. In the meteorological parameters, which include solar irradiance and panel temperature, these two parameters affect the solar panel's energy mostly [9,10,22]. A major portion of solar radiation is absorbed by solar panels instead of converted to electrical energy and is absorbed by the solar panel, thus increasing the panel's temperature [21,23]. This increase in the solar panel's temperature affects its current–voltage characteristics, known as the IV curve [12]. The solar panel's output current is directly proportional to solar irradiance with little effect on the output voltage [8,10,12]. The panel's temperature has a positive impact on the panel's output current while having a negative impact on output voltage [8,10,12,21,23].

Other meteorological parameters are considered as second-order factors with a lesser impact on an individual solar panel's electricity output. Ambient pollution and panel soiling do affect a solar panel's electricity output [5]. These parameters are not significant in areas with ample rains but have to be countered with frequent cleaning in dryer regions.

2.2. Electro-Physical Parameters

Constantly changing meteorological parameters can cause fluctuations in a solar plant's electricity output. Hence, it is imperative to monitor the solar plant's electro-physical parameters for better fault diagnostics. Generally, the main electrical components of solar plants are [8,22]:

- Solar panels which produce a direct current (DC).
- Inverters that transform DC into alternating current (AC) [24].
- Batteries for electrical energy storage.

A solar array contains multiple integrated solar panels with each panel having 36–72 cells/panel. With an average lifespan of 20–25 years, typical historical averages of solar panel degradation have been reported at about 0.8% per year [12,24]. However, the primary maintenance issue arises with inverters, which have an average lifespan of 5–10 years [12,13]. Non-functioning and incorrect inverter sizes lead to reduced electricity generation, thus making it imperative to monitor electrical parameters at each level.

3. Conventional Architectures

Bosman et al. have categorized solar plant monitoring as (1) manual inspection, (2) failure mode and effects analysis, (3) machine learning and forecasting, and (4) IoT-based monitoring [12,25]. It was concluded that though IoT-based monitoring is the most expensive, it provides the highest accuracy [12,26]. In this context, numerous solutions have been proposed in the existing literature; we have presented these literature reviews in Tables 2 and 3 in detail. Efforts are afoot to provide low-cost, scalable, reliable, and efficient IoT-based monitoring systems. The computing architectures of these IoT solutions can be broadly categorized as either centralized or cloud-based. The underlying architecture of these solutions generally has four layers for both centralized and cloud-based solutions. These layers range from perception, network, support, and application layers [22], and are shown in Figure 2.

1. Perception Layer comprises actuating and sensing parameters at the panel or array level depending upon the proposed solution.
2. Network Layer is represented by wireless inter-networking (within a farm) or inter-networking (between solar farms and remote servers).
3. Support layer is where information is stored and processed and raw data are translated into valuable information.
4. Application layer provides an interface for clients, stakeholders, or researchers to offer insights into the viability of installed solar plants.

However, depending on solar plants' size and monitoring objectives, different proposed solutions make some of the layers redundant, and these redundancies are observed and presented in Tables 2 and 3 in detail.

Table 2. Centralized architectures in the existing literature.

Perception Layer		**Network Layer**	**Support Layer**		**Application Layer**	**Ref.**
Compute Board	**Sensed Parameters**	**Communication Technology**	**Gateway WebServer**	**Communication**	**Centralized Server**	
Arduino Nano	I_A, V_A, P_A, T_{mod}, B_S	-	-	-	Local Server	[27]
Arduino Uno	I_A, V_A, P_A	Bluetooth	-	-	Local Server	[28]
89C51	I_A, V_A, T_{amb}, G_i	XBee	-	-	Local Server	[29]
MSP430	I_A, V_A, B_S, I_B, V_B, P_L, I_L, V_L	GSM	-	-	Local Server	[8]
Arduino Uno	$I_A, V_A T_{mod}$	GSM	-	-	Local Server	[30]
Arduino Mega	I_A, V_A, I_L, V_L, P_L, P_A DC	Wi-Fi	-	-	Local Server	[31]
RPi 3	I_A, V_A, T_{amb}, I_L, V_L	Wi-Fi	-	-	Local Server	[32]
ATmega328p	I_B, V_B	Ethernet	-	-	Local Server	[33]
IOIO-OTG	I_A, V_A, P_A T_{mod}, I_B, V_B, I_L, VL	USB	-	-	Android Server	[23]
Arduino Uno	I_A, V_A, P_A, I_B, V_B, P_L	WLAN	-	-	Web Server	[34]
ESP32	I_A, V_A, I_B, V_B, I_L, V_L	Wi-Fi	-	-	Web Server	[35]
Arduino Mega	I_A, V_A, T_{mod}, G_i	Wi-Fi	-	-	Web Server	[36]
RPi 3	I_A, V_A	Wi-Fi	-	-	Web Server	[37]
Arduino Mega	I_A, V_A, G_i, T_{mod}, P_A	Wi-Fi	-	-	Web Server	[38]
-	I_A, V_A, P_A	Bluetooth	RPi 3B Local Server	-	-	[6]
Arduino Nano	I_A, V_A, P_A, G_i, I_L	RF	Arduino Nano	-	-	[39]
XBee Pro S2	I_A, V_A, P_A, G_i, T_{mod}, I_L, V_L	RF	XBee Pro S2	RF	PC(MATLAB)	[9]
Arduino Nano	I_A, V_A, P_A, G_i, T_{mod}, T_{amb}	LoRa	Rpi 3B	LoRa	PC(MYSQL)	[4]
ATmega328	G_i, T_{mod}, T_{amb} H, WS	RF	ATmega328	USB Port	PC(LABVIEW)	[40]
DSP-TMS320F28335	I_A, V_A, G_i, T_{mod}	Zigbee	Rpi 3	Wi-Fi	Web Server	[41]
Arduino Nano	I_A, V_A, P_A, I_B, V_B, T_B, I_L, V_L, I_C, V_C, T_C, T_{amb}, H, D	XBee Module	Arduino Uno	Wi-Fi	Web Server	[42]
Arduino Uno	I_A, V_A, G_i, P_A, T_{mod}, T_{amb}, H, WS, WD	RF	RPi 3B	RF	Web Server	[43]

Table 3. De-centralized (cloud-based) architectures in the existing literature.

Perception Layer		**Network Layer**	**Support Layer**		**Application Layer /Ref.**
Compute Board	**Sensed Parameters**	**Communication Technology**	**Gateway/ WebServer**	**Commnication**	**Cloud Plateform**
Arduino Nano	V_A, V_A, P_A, LI,G_i,D, H,T_{amb}	GSM	-	-	ThingSpeak [44]
Arduino Uno	V_A, P_A	Wi-Fi	-	-	ThingSpeak [45]
Arduino Ethernet	I_A, V_A, P_A, G_i, H, T_{mod}, WS, R,T_B, V_B, I_B, V_L	3G	-	-	ThingSpeak [15]
CC3200	I_A, V_A, T_{mod}, H,I_C	Wi-Fi	-	-	ThingSpeak [46]
Arduino Mega	I_A, V_A, T_{mod}, P_A,LI	Wi-Fi	-	-	ThingSpeak [21]
Arduino	I_B, V_B, T_{amb} H,P_A	USB	RPi 3	Wi-Fi	ThingSpeak [3]
RPi 3B	I_A, V_A, T_{mod} V_B, LI	Wi-Fi	-	-	Ubidots [7]
Arduino Uno	I_A, V_A, P_A, T_{mod} D,H,	Serial	NodeMCU	Wi-Fi	Ubidots [47]
Arduino Mega	I_A, V_A, P_A T_{amb}	Wi-Fi	-	-	Blynk App [14]
Arduino	I_A, V_A, P_A T_{mod}, H, I_L, V_L,D,Uv	Serial	ESP32	Wi-Fi	Blynk App [48]
NodeMCU	I_A, V_A, T_{mod}, A_T	Wi-Fi	-	-	AWS [2]
RPi Zero W	P_A, I_A, V_A, T_{mod}	Zigbee	RPi Zero W	Wi-Fi	[49]
Adafruit Feather M0	I_A, V_A, T_{amb}, H, I_B, V_B B_S, I_L, V_L	LoRaWAN	RPi	GSM	Ubidots [50]
Arduino Uno	I_A, V_A, T_{amb}, H,G_i, T_{mod}	LoRaWAN	RPi	LoRaWAN	The Things Network [43]
RPi	I_A, V_A, T_{amb} T_{mod}, D, G_i, H,P_L, P_A	Wi-Fi	RPi	Wi-Fi,GPRS 3G, 4G	AWS [20]

3.1. Centralized Architectures

The differentiating feature of a centralized architecture as compared to cloud-based architecture is the application layer. Sensor nodes at the perception layer act as fountains of data continually feeding a central entity. This central entity can be either a local or a web server, as presented in Table 2. These servers (local or web) centralize the generated information, processing it and combining it for different stakeholders. However, depending on the solar plant size or level of monitoring offered, some of the architectural layers can be omitted, which are shown in Table 2. For example, in [6,39], the application layer is discarded instead of using compute boards as a support layer for information dissemination. In [7,23,27,38], the support layer has been made redundant, while in [4,9,16,40–42], all four architectural layers have been implemented, and the details are presented in Table 2.

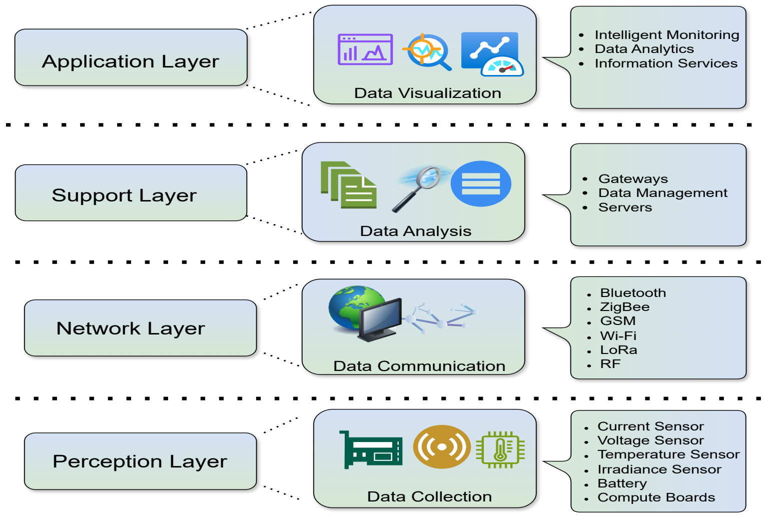

Figure 2. This figure describes the general architectural layout of IoT-based solar plant monitoring systems. It illustrates the four primary layers: the perception layer, which consists of end devices; the network layer, which lists the communication technologies for transmitting the collected data; the support layer, which involves gateways and data management; the application layer, which offers data visualization and monitoring tools.

3.2. Cloud Computing-Based Architectures

In a cloud-based architecture, the salient feature is the employment of a cloud computing platform at the application layer. Cloud computing platforms offer immense scalability potential in terms of big data management (data storage, processing, mining, analysis) as well as visualization and web application tools. In the existing literature, popular cloud computing platforms employed are ThingSpeak, Ubidot, and Blynk, which are presented in Table 3. Another advantage is MQTT (Message Queuing Telemetry Transport), which is a lightweight and secure protocol. MQTT, because of its advantages, is supported by most cloud service providers for managing large numbers of connected things.

In light of the existing literature review, it is evident that some design challenges have gone unaddressed in proposed solutions. By overcoming these challenges, improvement can be embedded with future IoT-based solar monitoring systems. Salient contributions of this work are:

- Effects of meteorological and electro-physical parameters on solar plant efficiency have been explored.
- Design paradigms for end and edge nodes have been proposed. The underlying design considerations are low cost, scalability, reliability, and big data management.
- An edge computing paradigm has been proposed to overcome associated challenges of centralized and cloud computing-based architecture.
- For big data management, a public cloud platform's architecture has been proposed.

4. Our Proposed Architecture for Smart Solar Plant

The conventional method of solar plant monitoring was either through manual inspection or a wired sensor network. The next revolutionary step was centralized IoT-based architecture. The performance of these solutions was seriously limited because of labor- and time-intensive work [51]. Furthermore, scalability, reliability, and cost were some of the other factors undermining the aforementioned solutions. However, recent advancements in technology (hardware, software, communication, and cloud computing) have made it possible to offer high-performance and cost-efficient monitoring systems. An IoT-based solar plant monitoring system consists of numerous geographically spread sensing devices. These devices sense their surroundings and transmit information periodically to a server for processing, storage, and analysis. Low cost, reliability, scalability, and security are some of the important considerations. For example, Begum et al. [5] reported that a fully functional 500 MW solar plant will have 2,500,000 solar panels (with each panel rated to produce 200 W). Sensing each solar panel's current, voltage, and temperature will generate nearly 8 Gb/s of data. As a result, the transmission, management and storage of this huge amount of data can be a challenging task.

Based on this context, a monitoring solution has been proposed based on edge computing paradigms. The proposed edge computing paradigm, integrating both IoT and cloud computing paradigms, is shown in Figure 3. At the perception layer, end devices are responsible for sensing each solar panel's electrical parameters. The data from the end devices are sent to the edge layer. The edge nodes are responsible for filtering the data from the end devices and fetching meteorological parameters. In the third layer, the cloud platform is responsible for data storage, processing, analysis, and information dissemination.

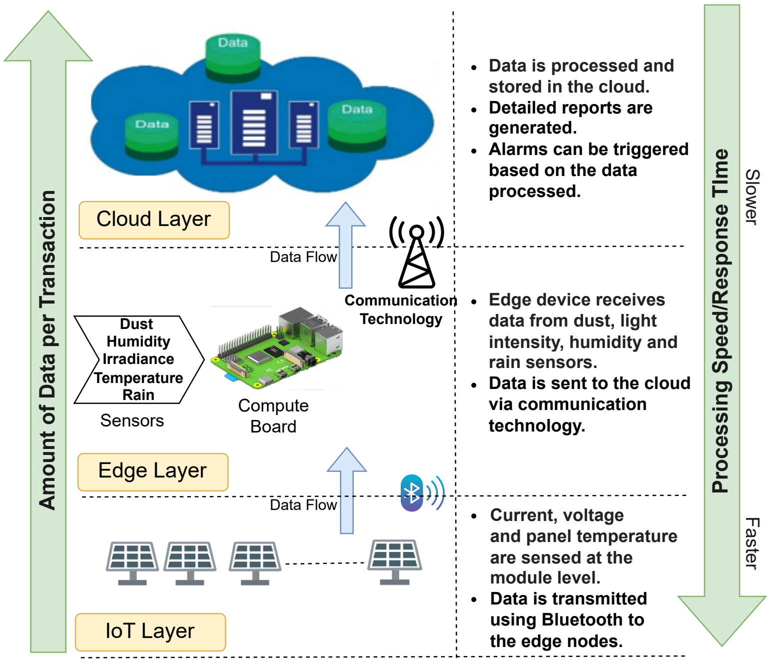

Figure 3. This figure illustrates a layered architecture for smart solar plant monitoring, integrating cloud, edge, and IoT technologies. It shows the hierarchical data flow from IoT sensors through the edge layer to the cloud for further analysis. The IoT layer consists of module-level end devices, while the edge layer consists of a compute board that receives data from these devices and processes data from various environmental sensors as well. Data collected at this layer is prepared for upward transmission to the cloud, where it undergoes further processing for detailed analytics.

4.1. Perceptual Layer

Depending upon the granularity of monitoring, solar plant monitoring can be performed at module, array, inverter, and battery levels. The end devices comprise the compute board, sensors, and communication module. Salient features to be considered in the design and development of end devices are:

- A low-cost system by using off-the-shelf hardware and open-source software.
- Power optimization for minimum human intervention.
- Flexibility from modification perspective [16,20].
- Scalability and independence from solar panel layout and configuration.

Data are collected from the physical world in the form of analog signals through different sensors. These signals (representing electro-physical properties) are converted to digital values and transmitted wirelessly to edge nodes.

4.1.1. Microcontroller Board

The choice of microcontroller board at the end is fundamental for sustainable design. The selection of the micro-controller board is based on parameters like computation power, embedded memory, power consumption, and communication capabilities. For power optimization, end devices mainly operate in sleep mode and wake up at user-defined intervals for data sensing and transmission [51]. In Tables 2 and 3, a comprehensive list of popular microcontroller boards for solar plant monitoring is presented, including Uno, Nano, Mega, and NodeMCU. In the majority of the proposed solutions, Raspberry Pi (RPi) has been employed as presented by [3,4,6,7,16,20,32,37,41,43,49,50]. However, RPi is not an optimum choice for end devices considering its monetary cost and power requirements. Arduino Nano is the optimum choice in the end because of its low cost, power requirements, and wireless communication support.

4.1.2. Sensors

Real-time data are the key component of any smart monitoring system, as such systems make smart and meaningful decisions about the system's operation and performance based on the real-time data. For solar plant monitoring, various sensors are integrated with Arduino Nano depending upon the component (solar panel, inverter, or battery). Some commonly sensed parameters range from current, voltage, panel temperature, ambient temperature, humidity, irradiance, and dust particles. Sensed parameters can be transmitted to servers at user-defined intervals (ranging from 1 to 30 min, hours, or days).The most commonly used sensors listed in the existing literature are presented in Table 4.

Table 4. Meteorological and electrical sensors employed in existing literature.

Type	Model	Cost	Range	Accuracy
Current Sensor	ACS712	USD 1	30 A	±30 A, output error of ±1.5%
	Yocto	USD 100	∼2 mA	1–3%
	INA219	USD 6	±3.2	0.2–0.3%
Voltage Sensor	INA219		0–26 V	0.2–0.5%
	LM24	USD 6	6–36 V	0.05 repeated precision
	Voltage Divider	USD 1	0–50 V	±1–±5%
Temperature	LM35	USD 3	−55–150 °C	10 mV/°C
	DHT-11	USD 2.50	0–50 °C	95%, ±2 °C
	DHT22	USD 105	0–100%RH; −40∼80 °C	0.05 ± 2%RH–5%RH, ±0.5 °C
	DSB18B20	USD 3	55 to +125 °C	+0.0625 °C +0.125 °C +0.25 °C +0.5 °C
Irradiance	LDR	USD 0.5	8–200 M ohm	
Dust	GP2Y1010AU0F	USD 12	0.5 V/0.1 mg/m^3	
Light intensity sensor	GY-49 MAX44009	USD 12	0.045–188,000 lx	15%
	BH1750	USD 2	1–65,535 lx	20%
Humidity	HM2301	USD 1	0–100%RH	±3%RH; ±1 °C

4.1.3. Communication Technologies

For higher accuracy and precision, component-level monitoring provides more granular data for assessment. This is in sharp contrast to the conventional measurement that occurs at central inverter levels. It is therefore recommended to install end devices at panel and inverter levels for better data analytics. These sensed parameters can then be transmitted to either a centralized server/storage or a cloud platform for data analytics. Although multiple communication technologies are available, the sheer size of a typical solar plant presents challenges for devising a wireless sensor network. The most prominent of these challenges is selecting a wireless technology that can meet the network requirements of such a system. This selection is made based on the range, operating frequency, topology, network security, power consumption, and cost of each communication module. We have analyzed the existing literature to identify the most commonly used communication technologies for monitoring, as detailed in Table 5.

Table 5. Comparison of different wireless communication technologies.

Technology	Operating Frequency	Range	Data Rate	Power Usage
BLE	2.4 GHZ	1–100 m	1–24 Mbps	1–100 mW (TX power of 4 dBm)
Zigbee	2.4 GHZ, 900 MHz and 868 MHz	75–291 m	20–250 kbps	1–100 mW (TX power of 18 dBm)
Wi-Fi	2.4, 3.6, 5, 6.5 and 60 GHZ	1–150 m	2 Mbps–6.7 Gbps	100–200 mW
RF	3 Hz–300 GHz	1 cm–105 km	Varies	Varies (typically low power)
6LoWPAN	2.4–2.48 GHZ	10–100 m	250 kbps	low power (similar to BLE)

Bluetooth [6,28] provides the highest bandwidth. However, the disadvantages are short distances and comparatively higher power consumption per bit transmission. The two viable options are Zigbee, observed by [29,41,42,49], and Wi-Fi, observed by [2,3,7,14,20,21,31,32,35–38,41,42,45–49]. On the basis of this review, Zigbee and Wi-Fi have the potential to create local wireless sensor networks.

4.1.4. Proposed Strategy at the End

For in-depth solar plant monitoring, it is imperative to sense performance parameters at each level (such as module, arrays, inverters, and batteries) for predictive fault diagnosis. However, cost (monetary and power consumption) is a major design consideration in the selection of end devices. Keeping in view these two parameters, a low-cost and power-efficient end device is being proposed, as presented in Figure 4. Arduino Nano BLE [27] has a 32-bit ARM Cortex M4 CPU operating at 64 MHz. This is enough computation power for sensing current, voltage, and panel temperature, as listed in Figure 4. Furthermore, it has an ultra-low power consumption mode with integrated BLE. This integrated BLE module with Arduino Nano BLE also helps in reducing the design complexity of the proposed end device. With 19 mA current consumption, this is the optimum choice with respect to cost and current consumption. To keep the overall cost low, it is proposed to integrate only current, voltage, and panel temperature sensing sensors with Arduino Nano BLE. For the current sensor, ACS712 is proposed, as this is the most popular choice in the existing literature [2–4,9,14,21,23,29,31,33,36,38,39,45,47,52]. Arduino voltage sensor [51] is proposed for voltage sensing. LM35 [2,7,9,21,23,29,30,32,36,52] is proposed for integration for the solar panel's temperature sensing. As can be observed in Table 6, the proposed power-efficient end devices can be fabricated at a cost of approximately USD 25.

Sensed parameters from end devices at different levels (panel, array, inverters, and battery) can be sent to edge nodes at the edge layer. To keep the overall cost of end devices low, meteorological sensors (such as dust, irradiance, temperature, and humidity) should be integrated with edge nodes only. This is also instrumental in reducing data transmission requirements from the perception layer to the edge layer, thus resulting in reduced current consumption requirement at end nodes. As presented in Table 5, the range of BLE is low as compared to other wireless technologies. However, in our proposed architecture, the edge devices will be within the 100 m range of end devices.

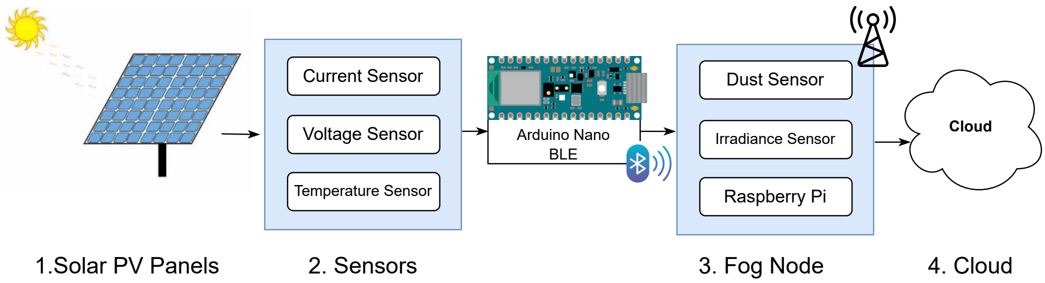

Figure 4. Our proposed system-level architecture is composed of end devices (sensors and a compute board). The data from the end devices are transmitted to the edge layer (fog node) via Bluetooth. The edge layer consists of a few meteorological sensors and communication technology for sending the data to the cloud for further processing.

Table 6. Cost and current consumption of proposed edge device.

Modules	Cost (USD)	Current Consumption (mA)
Arduino Nano	20	19 mA
ACS712	1	0.05 W
Voltage	1	
LM35	3	0.24 mW–1.8 mW
Total	25	

4.2. Edge Layer

The edge layer is an intermediate level employed for real-time analysis and big data management. Being an example of distributed computing, it is intended to complement cloud computing rather than substitute it. The end devices (integrated with solar panels, inverters, and batteries) will produce voluminous data for data analysis and predictive fault diagnostics. The idea of the edge layer is to process raw data in order to reduce the volume of data transmitted to the cloud platform, thus resulting in reduced data bandwidth requirements and transmission costs. Furthermore, for historical performance analysis, solar plants' performance parameters are stored to generate periodic reports. Therefore, the problem of logging huge amounts of data has to be taken into consideration in the architecture paradigm design [53]. In the existing literature, RPi has emerged as the most optimum choice for gateway (edge/fog nodes) devices, as presented in Tables 2 and 3. RPi is a credit card-sized single-board computer offering approximately the same functionalities as that of a desktop computer [17]. It is relatively cheaper and easier to operate, as well as supporting various operating systems. It is used extensively in automation and IoT projects because of its ease of operation and built-in support for communication technologies such as Bluetooth and Wi-Fi. For overall cost optimization, the meteorological sensors should be integrated at the edge nodes only, as presented in Figure 5.

In the existing literature, various wireless communication technologies have been employed for data transmission to remote servers. These technologies range from LoRA [4,43], LoRaWAN [50], RF [9,16,39], and Wi-Fi [3,7,14,20,21,42,45–48]. However, to reduce network complexity and the ubiquitous presence of cellular towers in remote locations, GSM technology (SIM900) is the most optimum solution for edge nodes. The deciding factor for this choice is based on the range it offers, as solar plants are mostly located in isolated and remote regions. Furthermore, cellular networks offer long-range, affordable, reliable, and scalable data transmission networks. For example, in South Asia, a 6000 MB internet data package is available for USD 5 [52]. In this regard, SIM900 [8,15,30,51] can be employed for intercommunication between edge nodes and requisitioned cloud platforms.

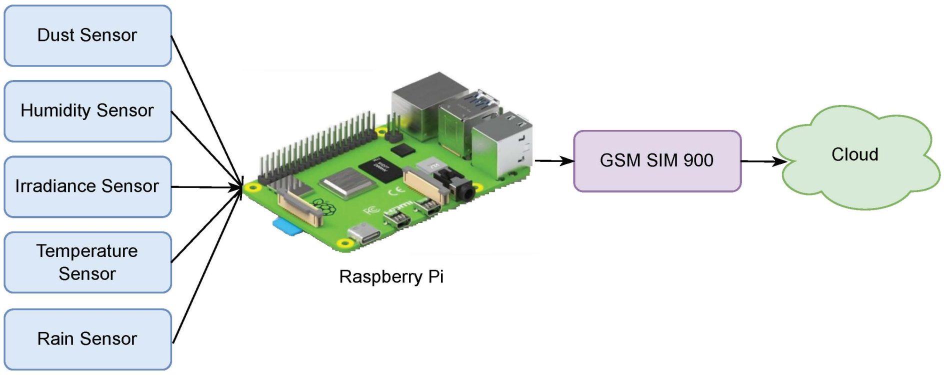

Figure 5. This figure shows block diagram of the end node, comprising a few meteorological sensors, a compute board, and a communication technology (GSM) for data transmission to the cloud.

4.3. Cloud-Based Implementation

A huge amount of data is generated through solar plant monitoring, making data management a pressing issue from a sustainability perspective. For example, it was reported that 8 Gb/s of data will be generated by a 500 MW solar plant (with 2,500,000 solar panels each rated to produce 200 W) [5]. Although data cleansing techniques can be employed at the edge layer, monitoring the data is still a huge task for any local server, thus necessitating the employment of cloud computing platforms. In the application layer, these accumulated data are regulated, cleansed, and archived for analysis, as can be seen in Figure 3. Furthermore, an interface is provided for users and stakeholders to access, manage, and perform data analytics for fault diagnostics and information dissemination. In this context, cloud platforms have emerged as the optimum solution for application layer deployment. The salient features of cloud platforms are their high availability, reliability, and scalability. Furthermore, they provide a variety of network services, hardware resource virtualization, and scalability to handle huge amounts of data exchange, sharing, and management [53]. The most common cloud platforms employed for solar panel monitoring in the existing literature are detailed in Table 7. It provides a detailed profile of the cloud platforms mentioned in the literature. It lists the communication protocol supported by each platform, openness, security mechanism employed, write rate, and list of compatible devices. It also highlights whether the platform has an option for messaging/notification services such as email, SMS, or Twitter. To explain further, write rate refers to the interval frequency at which data are sent to the platform, e.g., ThingSpeak sends an update every 15 s and Blynk sends updates every second. For other platforms such as Ubidots, AWS, and ThingsBaord, the data rate may vary, depending on the deployment and configurations. Regarding the notification service, some platforms may not have native support for a notification service but it can be integrated through an external service or an API, denoted by '(ext-int)' in the table. These attributes are crucial to compare cloud-based IoT platforms on various technical needs. Selecting the appropriate platform will help the design architect to steer the technology according to the project technical requirements and limitations.

These commonly employed cloud platforms such as ThingSpeak, ThingsBoard, Blynk, and Ubidots are both open-source and free to use but these platforms have serious limitations such as the number of maximum connected nodes, data upload rates, and the number of requests or messages per second. The public cloud platform Amazon Web Services (AWS) is therefore proposed for its capabilities, rich support and documentation, and the variety of tools that it offers. The choice of cloud platform depends on personal preference and may vary according to the project-specific needs. In our proposed architecture, we are going with AWS because it offers a comprehensive suite of services offering integration options with other AWS services and other third-party applications, robust security, dynamic scaling to support large-scale systems, tools for AI/machine learning, and other managed services like AWS IoT Core, AWS IoT Analytics, and AWS IoT Greengrass, which are specifically tailored for deploying, maintaining, and scaling IoT infrastructures.

Table 7. Characteristics of cloud platforms employed in existing literature.

Performance and Service Provided	Cloud Platform				
	ThingSpeak [7,21,34,39,40]	Blynk [12,39]	Ubidots [6,38,48]	AWS [15,20,36]	ThingsBoard [54]
Protocol	HTTP	HTTP, Ethernet, GSM	HTTP, MQTT	HTTP, MQTT	HTTP, MQTT, CoAP
Security	API Keys	SSL/TLS	TLS	SSL	SSL/TLS
Openness	Open-Source	Open-Source	Open-Source	-	Open-Source
Write Rate	15 Seconds	1 Second	Varies	Varies	Varies
Device Supported	Arduino, RPi	Arduino, RPi	Arduino, RPi	Arduino, RPi	Arduino, RPi
Email	Yes (ext-int)	Yes	Yes	Yes	Yes
SMS	Yes (ext-int)	Yes	Yes	Yes	Yes
Twitter	Yes	No	No	Yes (ext-int)	Yes (ext-int)

Using AWS serverless IoT, sensed parameters can be employed for information processing and analysis to generate desired reports for performance evaulation. The AWS IoT can be combined with other services such as event-driven rules, lambda, DynamodB, S3, kinesis analytics, and AWS Cognito to offer a secure, low-latency, and cost-optimized solution, thus helping in fault identification and diagnostics, predictive maintenance, and performance analysis.

4.3.1. Amazon Web Services

For big data management, a general AWS architecture is presented in Figure 6. The edge nodes transmit the sensed data to the AWS IoT core at user-specific intervals or upon any initiated event. The messages from individual edge nodes are first authenticated at the AWS IoT Core. Depending upon the message's type, location, and time, an appropriate predefined rule (in Rule Engine) can be implemented. The Rule Engine is responsible for routing the incoming message/data to the desired back-end application in the cloud. The AWS Kinesis Firehose encrypts the data and loads them to the Kinesis Analytics, where the data are further processed for anomaly detection, as shown in Figure 6. The data from the Kinesis analytics are used to predict system behavior and overall performance. Different scenarios can be initiated depending on the analytical results of incoming data/messages.

Scenario 1: No Anomaly Detected

If the received performance indicator values are within the desired user-defined threshold, the solar plant's performance is rated as satisfactory. Performance indicator values are theoretical solar panel output values, calculated considering the prevailing meteorological conditions. In such a case, a Lambda function can be triggered to store the data in the DynamoDB for archiving, as presented in Figure 6.

Scenario 2: Anomaly Detected

If the received performance indicator values deviate from the predefined threshold, it can be safely concluded that a part or some parts of the under-observed system are not working properly. The reasons can range from a faulty inverter panel, loose wiring connection, panel's soiling or orientation, and lower irradiance, to name a few.

Two different functions can be generated upon anomaly detection:

- A Lambda function can be invoked that stores performance indicator values in the DynamoDB and triggers the AWS Simple Notification Service (SNS) to notify the stakeholders.
- Diagnostic analysis can be performed using AWS Kinesis Stream to pinpoint the anomaly against trouble codes. A Lambda function can be invoked to store the trouble

codes in the DynamoDB tables and an SNS notification can be triggered with the translated trouble code.

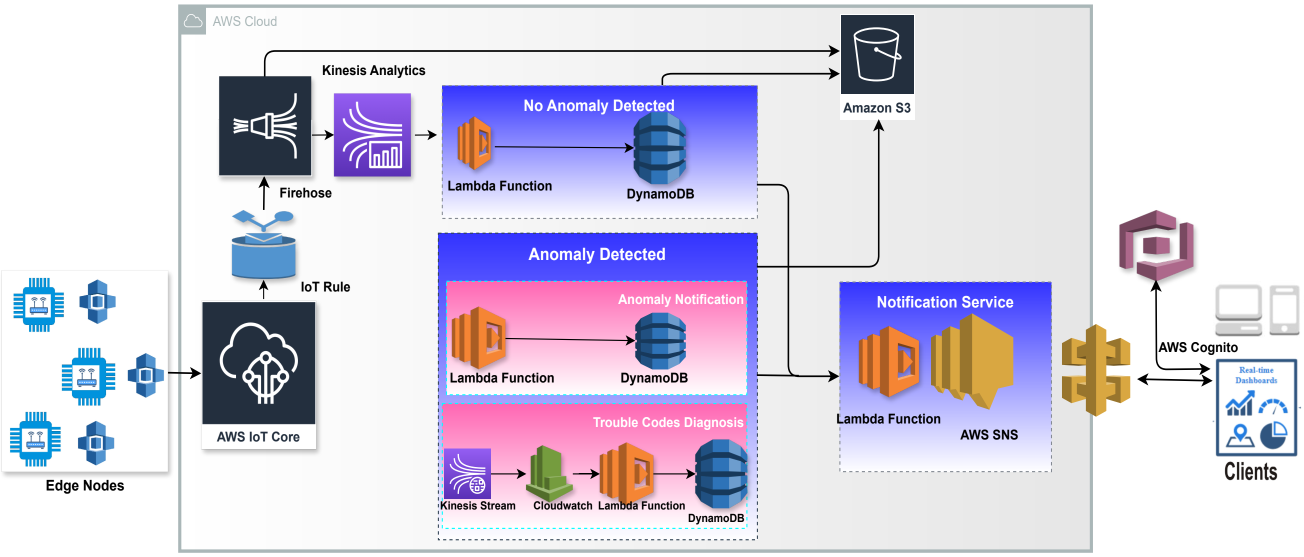

Figure 6. AWS infrastructure architectural overview for solar plant monitoring. This figure demonstrates the integration of AWS services involved in smart solar plant monitoring systems. Data flow from edge nodes through AWS IoT Core and are processed using Kinesis Analytics to detect anomalies. Depending on the analysis, notifications are sent via AWS SNS, and the data are stored in Amazon S3 for further use. The AWS Cognito facilitates secure access to user dashboards for monitoring and decision making.

The system can interact with the outside world securely and efficiently through the Amazon API Gateway, which hosts RESTful APIs and deploys the Amazon Cognitive user pool. The Amazon Cognito service authenticates users to make a request via the API Gateway. In turn, a Lambda function can be invoked to perform the desired task on the data stored in the DynamoDB tables. The RESTful APIs allow the existing applications and other third-party applications to interact or access the data in DynamoDB securely. These data can be used by the user to build detailed monitoring reports, graphs, and other performance evaluation charts.

The performance of solar plants depends on various meteorological and electrical parameters. Any fault in the system may lead to under-performance or system failure. Therefore, a refined and sophisticated algorithm needs to be in place for fault diagnostics and predictive maintenance. In this context, several artificial intelligence (AI)-based supervised learning algorithms have been proposed in the existing literature. The ANN technique is widely used for fault identification and classification [24,25,55]. In [38], the Artificial Neural Network (ANN)-based solar monitoring algorithm has been presented to predict the output power of heterogeneous solar plants. The proposed algorithm is trained on the solar panel's power, temperature, voltage, and solar irradiance. A solar panel is marked as faulty if the predicted power output differs by more than 10% from the actual solar panel's output power.

5. Artificial Intelligence in Solar Plant Monitoring

Artificial intelligence (AI) can perform a vital role in the monitoring, analysis, and management of solar PV systems. The solar plants are mostly installed in remote areas, while ensuring optimal energy generation, predicting and preventing system failures, and maintenance of the solar plants is crucial.

5.1. Artificial Neural Networks

In the literature, the application of AI, specifically supervised learning techniques empowered by Artificial Neural Networks (ANNs), has been reported by [25]. ANNs comprise interconnected nodes (neurons), which have similar structures and functions to the human brain. ANNs make the data suitable for analyzing complex data by learning the patterns and relationships in the data. These models are trained on relevant parameters and historical data and hold great promise for accurate fault diagnosis, classification and prediction, predictive maintenance, performance projection and optimization, and performance degradation of the solar plants [24,55].

The authors in [38] have proposed a solar plant monitoring algorithm using ANN for output power prediction of heterogeneous plants. Various parameters, like solar panel power, temperature, voltage, and solar irradiance have been considered for feature selection and used for training of the neural network-based models [56]. The algorithm classifies a solar panel as faulty if the predicted power output deviates by more than 10% from the actual output; otherwise, it is classified as no-fault. The predicted power output is used on a baseline to detect potential faults, underperformance, or deviating behaviors in the system [57].

Additionally, convolutional neural networks (CNNs) are mainly used in the image processing domain; however, CNN has also been used in the monitoring of remote solar plants [58]. CNNs extract features from images, which can be helpful in locating faults, performance estimation, soiling on the panels, and shadowing effects [59,60].

5.2. Feed-Forward Neural Network

Feed-forward neural network (FFNN) techniques in the literature have been used for diagnosis in PV systems [37,61–64]. The authors in [37] show an accuracy rate of 97.2% by predicting power output drops caused by short open-circuit faults, arrays and string degradation, and shadowing. However, FNNN is reported to have limitations, such as slow training, and risk may be involved in converging to local minimum points instead of the global minimum [37]. To mitigate the limitations in FNNN, Extreme Learning Machines (ELMs) are a suitable alternative and a neural network architecture for fault diagnostics in solar plants reported by [41]. In this work, the ELMs have successfully predicted fault diagnosis for open short circuits and shadowing. The ELMs are trained using historical power generation records and the sensed parameters of the panels, like current, voltage, output power, temperature, and irradiance. Some studies have integrated AI algorithms with additional techniques, such as data fusion and feature engineering for improving fault diagnosis and maintenance in solar plants [65].

5.3. Role of AI in Solar PV Systems

Artificial intelligence (AI) can perform a vital role in the monitoring, analysis, and management of solar PV systems. AI can be beneficial in the following ways in the context of solar PV systems:

1. **Predictive Models:** AI will facilitate the development of predictive machine learning models for optimizing renewable energy usage and reducing environmental impact [66]. The authors developed a prediction model for PV systems that measures weather irregularities. Their dataset for training and testing consists of a plant inverter and the weather measurement system and used different machine learning algorithms, including linear regression, random forest, principal component analysis, and support vector regression with RBF kernel to examine the data and create a model that can accurately predict the power output [66].
2. **Performance Optimization**: AI algorithms can make intelligent decisions based on the data collected by different sensors involved in the solar PV systems and the historical data to optimize the performance of the plant by adjusting the tilt angles of solar panels according to the sun's movement or a cleaning mechanism can be installed in place if there is dust on the panels [67].

3. **Anomaly Detection:** In modern solar power plants, AI has been used for anomaly detection [68]. A recurrent neural network (RNN)-based model called AutoEncoder Long Short-Term Memory (AE-LSTM) based on the Genetic Algorithm (GA) as a hyperparameter tuner was applied to detect anomalies in two power plants. The authors demonstrated outstanding accuracy in detecting anomalies and compared them with the Isolation Forest (IF) and the Local Outlier Factor (LOF) methods [68].
4. **Energy Forecasting:** AI has been used in energy forecasting, by utilizing different machine learning algorithms including linear regression, random forest, principal component analysis, and support vector regression [69]. These algorithms are trained using historical meteorological data to estimate power plant solar energy generation.
5. **Predictive Maintenance**: AI can help the operator to take proactive measures for maintenance and minimize downtime by alerting the operator in real time through malfunction as well as fault detection or degradation in real time. AI algorithms can locate an underperforming panel and identify anomalies by analyzing data patterns and comparing them to the expected outcome [67].
6. **Energy Demand Forecasting and Operational Optimization**: Through AI, vendors can achieve grid stability, energy optimization, and reduce unnecessary energy wastage by analyzing historical data and weather patterns. The data-driven decision of AI can be helpful in grid integration by analyzing the energy demands and supply in real time, ensuring a smooth and cost-effective supply of power, low downtime, balanced generation, and balanced consumption.

The selection of the AI model is based on different parameters like the monitoring tasks to be performed on the available datasets and the chosen predicted outcomes. Different aspects may suit different models and broad monitoring and optimization can be achieved by the combination of different AI models.

6. Discussion

This study aims to evaluate the effectiveness (in terms of cost, efficiency, and reliability) of a novel, cloud-based architecture for monitoring solar power plants by leveraging the Internet of Things (IoT), edge computing, and cutting-edge technologies, e.g., cloud computing and artificial intelligence (AI). We proposed that the low-cost design approach successfully balances the trade-offs between cost and performance using minimum hardware resources, e.g., sensors and compute boards, and present the best technological practices that will serve the needs of both small-scale and large-scale solar PV plants. The fog/edge layer preprocess the data before sending them to cloud platforms like AWS, reducing latency and bandwidth usage. We proposed and established evidence, which includes the fact that the integration of the edge layer is pivotal in managing the intermittent nature of solar energy and their sensitivity to environmental changes accurately in real time and with the least overhead and cost. The proposed system integrates cloud, edge, and AI technologies, which not only meet operational needs for handling the massive data generated by the monitoring system but also ensure affordability and accessibility, making it viable for wider adoption in the solar industry.

We have presented a literature review on the existing architectures (centralized and de-centralized), hardware resources, and communication technologies. These architectures have shortcomings, including (1) the use of proprietary software, (2) being expensive or not easily available hardware, (3) limitations in communication technologies, and (4) dependency on a specific technology chosen for implementation. As a result, it makes them less generalizable, less cost-effective, and prone to failures to be applied in other platforms or large-scale industrial systems. Moreover, previous studies highlight the potential of cloud computing in solar plant monitoring systems but miss the context of synergy between edge computing and cloud services. This potential gap is filled by proposing an edge layer that preprocesses the data before sending them to the cloud and then implementing AI-based analytics directly within the cloud architecture. Our focus in this article includes (1) the cost and simplification aspect of the architecture, (2) detailed monitoring, and (3) system insights, which can be achieved by increasing the number of sensed parameters but that will incur some additional cost and complexity. Also, there could be a potential risk of data loss or over-simplification during preprocessing at the edge layer, omitting some valuable insights.

Future explorations in the context of this research can be performed on the economic analysis of scaling the system across different geographical and climate conditions. Moreover, the evaluation of durability and maintenance requirements of the devices at the perception and edge layer can be explored in future. Further investigation can be carried out into the integration of other renewable energy sources. Cloud computing and AI are already dominating the modern technological world and new tools and technologies are frequently evolving. Exploring further cloud computing platforms/technologies and AI models that can leverage such IoT systems can be a rich avenue for further research.

7. Conclusions

In this work, advances and associated challenges in IoT-based solar plant monitoring have been explored. Furthermore, an in-depth review and analysis of different computing paradigms (centralized and decentralized) employed has been performed. Underlying technologies (such as compute boards, sensors, communication and cloud platforms) employed as building blocks for these solutions have been reported and analyzed. This comparative analysis was undertaken based on cost-effectiveness, power efficiency, scalability, reliability, big data management, and operation under harsh environments. It has been concluded that a balance needs to be maintained between levels of monitoring (such as a solar panel, array, or inverter level) and cost incurred in terms of additional hardware requirements, thus increasing the overall monitoring system cost. It was observed that the proposed solutions in the existing literature are either expensive or too complicated for implementation. Furthermore, these solutions provide little support for customization or are designed to address only small-scale systems. In this context, an edge computing paradigm has been proposed, which offers greater scalability, big data support, improved monitoring tools, and enhanced security. Suggestions have been made for low-cost and power-optimized end and edge device fabrication. As meteorological parameters do not vary much from solar array to array, it has been proposed to integrate meteorological sensors at edge nodes instead of at individual panels. To keep overall design complexity and data transmission requirements low, it is proposed that data management should be implemented at edge nodes. As opposed to free and open-source cloud platforms, it was concluded that public AWS is a better choice. Salient contributions range from greater support and tools for IoT systems with enhanced security to a notification and alarm system to notify the user of any unpredictable behavior. As a future consideration, this work can be used for grid integration and smart metering, which will offer improved operating strategies, enhanced power plant scheduling, energy forecasting, and flexible generation and storage. It can play a vital role in a country's economy by filling energy demand gaps as well as mitigating GHG emissions and tackling climate change.

Author Contributions: M.I.A. prepared the structure of the paper with K.S.K. and wrote the primary draft with S.D. M.I.A. has performed an in-depth literature review and conducted an analysis of the techniques proposed in the paper. M.I.A. and R.M. wrote the primary part of the paper and revised it with respect to comments from S.D. and K.S.K. Moreover, S.D. also assisted in modelling and implementing the figures of the paper in an appropriate way. M.I.K. and R.M. have critically reviewed the paper, assisted the team in refining and finalizing the final draft, and suggested some changes. All the authors read, reviewed, and took part in different sections of the paper to make the final version. All the authors have approved the content of the paper to be submitted to this journal. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: We have checked first individually and later declared that all authors have no conflicts of interest to disclose.

Abbreviations

Renewable Energy Source (RES), Greenhouse Gas (GHG), International Energy Agency (IEA), IoT (Internet of Things), Total irradiance (G_i), Ambient Temperature (T_{amb}), Module Temperature (T_{mod}), Wind Speed (WS), Wind Direction (WD), Humidity (H), UV Radiations (Uv), Angle of Tilt (A_T), Output Voltage (V_A), Output Current (I_A), Output Power (P_A), Output Energy (E), Duty Cycle (DC), Grid Voltage (V_U), Current To Utility-grid (I_{TU}), Power To Utility-grid (P_{TU}), Power From Utility-grid (P_{FU}), Utility Grid Impedance (Z), Load Voltage (V_L), Load Current (I_L), Load Power (P_L), Battery State (B_S), Battery Current (I_B), Battery Voltage (V_B), Battery Temperature (T_B), Controller Current (I_C), Controller Voltage (V_C), Controller Temperature (T_C), Network Time Protocol (NTP), Direct Current (Dc), Alternating Current (AC), Message Queuing Telemetry Transport (MQTT), Amazon Web Services (AWS),Simple Notification Service (SNS), Artificial Intelligence (AI), Artificial Neural Network (ANN), Feed-Forward Neural Network (FFNN).

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