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A Review on Solar Photovoltaic Power Plant Monitoring

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ABSTRACT: Concerns about the global environment and rising energy demand, coupled with steady advances in renewable energy technology, create new opportunities for the use of renewable energy resources. Photovoltaic technology is one of the best ways to harness the energy of the sun. This paper outlines regular inspections of solar panels are important to extend their lifespan and ensure the performance of their solar systems. Intelligent surveillance and control systems allow you to take advantage of the maximum solar potential of your photovoltaic system. Surveillance and control systems are rapidly gaining popularity due to their easy-to-use graphical interfaces for data acquisition, monitoring, control, and measurement.

Keywords: Monitor system and solar photovoltaic technology.

I. INTRODUCTION

To monitor system performance, especially in renewable energy applications such as photovoltaic, that used a data collection system to collect all data related to the installed system. This document provides an overview of solar system monitoring systems by discussing solar system architecture, solar system issues, and solar system monitoring techniques. Since solar systems are usually built in remote locations, it is difficult to provide a team of experienced site engineers to continuously monitor the solar system. Solar arrays also include a variety of devices such as inverters, solar panel strings, transformers, meteorological stations, and energy meters. The total energy production and performance of the array depends on how well this diverse configuration is maintained over the long term. Other factors such as dust, bird droppings, smoke, dew, dirt, cable breaks, inverter failures, panel hotspots-these factors reduce power generation performance and reduce production by almost 20%. In addition, energy generation depends not only on the performance of the equipment, but also on external factors such as the amount of solar radiation and ambient temperature. Intelligent real-time monitoring and monitoring is required to assess system performance and identify inefficiencies in a timely manner. Reduce equipment downtime with a maintenance system that incorporates external contextual information (weather conditions, dust levels, etc.) and can identify equipment malfunctions. The world seems to be moving fast every day. Individuals and spots are becoming more and more connected, and individuals and groups are responding at an ever-increasing rate. Devices are deployed to push the boundaries of human responsiveness, prepare, analyze, and present an unlimited amount of information available to decision makers, and in some cases respond to events that occur [1-4]. There are different perspectives that distinguish streaming data from other types of information. The three most important are the difficulties presented by the constant nature of information, the free and changing information structure, and the high cardinality measurements. Information is always accessible and new information is constantly being created.

This has several implications for the configuration of the research and evaluation framework. In the first place, the assembly itself needs to be robust. Critical storage framework downtime means that information is lost forever. This should be taken into account when planning a real-time system. Second, the way information is streamed continuously means that the framework needs to be able to keep recognizing the information. If it takes two minutes to process a piece of information, the frame will not stay constant for a long time. After all, the problem is so terrible that you'll have to drop some information to keep up with the time the framework was lost. It's not enough to have a framework that cans only continuously "catch up" information. You should be able to process information much faster than continuous. All or part of the framework fails for certain reasons, such as ordered downtime, or unfortunate disappointment, such as a system failure. Real-time systems need to be able to handle and maximize the changes in available dimensions. Real-time architecture, by its very nature, is a layered system that relies on multiple loosely coupled systems to achieve its goals [5, 6].

Key components of a solar system are photovoltaic modules, strings, string monitoring boxes, inverters, and energy meters. Strings can be defined as an array of solar panels, and each string has multiple solar panels that generate solar energy.

These strands are connected in parallel with each other. Therefore, the energy produced by these strings is about the same given the same amount of solar radiation. String monitoring boxes can collect data from individual strings, and these string monitoring boxes are connected to an inverter. There are several such inverters. In a surveillance system, data is collected from all these devices using one or more data gateways. This data can be processed and visualized locally or sent to the cloud infrastructure for more advanced analysis and visualization. There are many types of failures that can occur with an inverter. Inverters do not generate power due to system failure, data loss due to communication errors, cloudy weather can affect production. Inverter manufacturers provide several alarms for error conditions displayed on the dashboard of each inverter or on a site server with a SCADA system. Onsite technicians are currently reviewing this data to manually identify the error. However, this requires a lot of manual intervention, resulting in suboptimal plant performance and a reduced return on investment. Therefore, we need an automated system that detects such errors in near real time.

II. LITERATURE REVIEW

Photovoltaic monitoring generally refers to detecting normal and unhealthy conditions when the performance of a system deviates from the desired performance. You can also classify and identify location errors. Monitoring schemes for photovoltaic systems are often recommended due to the often rough and constantly changing environmental conditions and the increasing complexity of Photovoltaic systems. Traditional manual operation is used to monitor photovoltaic and detect faults. This is time consuming, inaccurate and dangerous to the user. Current monitoring techniques are fast, accurate and safe for users. Monitoring systems are commonly used in large photovoltaic systems due to their high operating costs; but recently some low-cost monitoring techniques have also been implemented. These low-cost monitoring technologies are extremely useful for home and individual consumers [17-20]. This section details various modern solar array monitoring systems and data analysis methods for fault detection. In recent years, several surveillance systems for the solar system have appeared. In order to monitor the power generation of the solar array, it needs to be integrated with the photovoltaic power generation system on the grid. The author developed a monitoring system using Labview [1]. Another system was developed a solar photovoltaic with a wireless sensor and a central management server [2]. They used wireless sensor boards and text messaging transmission over cellular networks. The sensor boards and text messaging is sent to a central management system that hosts the sensor boards and text messaging and publishes remote measurement trends over the Internet. Another paper reported the more advanced photovoltaic management system. Since the generation of photovoltaic systems varies from time to time, it was generated using a subset sum problem algorithm with additional features for advanced remote sensing, auto-load, control, and priority-based switching. The power load can be adjusted dynamically [6].

A low cost wireless surveillance system is used for the remote PV array. As the number of photovoltaic modules increases, so does the demand for cost-effective wireless surveillance systems. Frequency Shift Keying is typically used to send data over wireless media from a remote station to an operator. Frequency Shift Keying offers better communication and less complexity than other methods. Recently, Frequency Shift Keying has become popular due to its low power consumption and wide area network. Panel parameters such as voltage and current are monitored and converted to digital format using an analog to digital converter. Frequency Shift Keying communication used this digital format for data transmission. This surveillance scheme has recently become more popular with the advent of the internet of things, increasing the reliability of the system [13].

The author worked on rotor data, prepared a Fast Fourier Transform, and processed time series using averaging and time adjustment techniques [7]. Another author continued his previous work to detect early signs of motion rotor anomalies using time-series prediction-based control charts and autoregressive models. They train the model with signals related to the normal behaviour of the rotor in motion, compare the behaviour of the signals to the trained dataset, and use alarms to represent system changes [8]. They conducted a mechanically triggered investigation by notifying a signal that was more noticeable than movement. In their article, they were will looked at data from two different nodes: strings and inverters. At the string level, instead of using correlations to detect unexpected behaviour and triggering an alarm after an anomaly notification is triggered in the form of an email or text message when a threshold is crossed, a threshold set the value. At the inverter level, we used data from the inverters from the last 6 months to understand the behaviour of various parameters and defined the model based on this. If the parameter value is not as expected, it is considered abnormal and an email and text will be sent. The message is triggered. Instead of extracting the data directly, as they suggested extracting the pattern from the topology graph of the Markov model [11]. They found five different patterns using three forms of Markov models. They proposed a variable-length hidden Markov model that is more versatile for mining different patterns than other models. The author proposes a new anomaly detection algorithm for real-time streaming applications based on the online sequence storage algorithm Hierarchical Temporal Memory [5]. The Hierarchical Temporal Memory algorithm can detect spatial and temporal anomalies in predictable and noisy areas.

The author provided a comprehensive overview of time series anomaly detection and proposed a new transformation of univariate time series that takes advantage of changes in subspace structure [7]. For clustering time series data, the author has proposed a Gecko clustering algorithm, which uses the proposed L method to determine a reasonable number of clusters [16].

The open source anomaly detection package created by Twitter can detect local and global anomaly using the Seasonal Hybrid ESD algorithm [9]. Yahoo has developed EGADS [10]. This is a popular open source time series anomaly detection algorithm that can automatically monitor various time series data and trigger alerts. Luminicolis a Python library that supports anomaly detection and correlation and can detect the cause of anomalies [13]. EGADS and Twitter anomaly detection algorithms can detect both spatial and temporal anomalies, and Luminicol can detect the root cause of the anomaly. Artificial neural networks are advanced technologies combined with traditional methods of automated error detection. An artificial neural network has a wide range of applications. Error detection, load prediction, and economical load balancing are some of them. Due to its self-learning properties, artificial neural networks provides better results than other advanced methods. Artificial neural networks have the ability to learn from experience. A multi-layer feed forward artificial neural network is used for automatic failure detection and prediction. This is the fastest and most accurate method. The sensor is not needed due to its low accuracy. Measured parameters such as temperature and irradiance applied to the input layer of the artificial neural networks. An artificial neural network compares the measured parameters with the actual parameters. If the comparison is violated, explain the error and detect the location of the error [12]. Forecasting solar radiation is generally important in planning the operation of a power plant. Solar irradiance is basic information in many areas. Recently, several studies for predicting solar irradiance on various time scales are based on artificial neural networks, fuzzy logic, and hybrid systems [18].

Maximum power point tracking of photovoltaic arrays is required to optimize conversion efficiency under varying amounts of solar radiation and non-uniform conditions. To change the maximum power point tracking efficiency in PV harvesting, the author proposed a new maximum power point adjustment scheme based on the identification of model parameters [15]. The recommended scheme can separate the maximum power point search from the converter behaviour and identify the most important parameters of the environmental conditions. Separation and restoration of virtual P-I curves in the controller. The author proposed a IPSO-based maximum power point method for tracking when maximum power point is presented with shadowless or shaded irradiance [14].

III. PROBLEMS IN SOLAR SYSTEM MONITORING

Solar systems are huge. They need 5 acres of land to set up a 1MW system. Manually monitoring such a system is time consuming and inefficient. Plants are built in remote areas and it is difficult to secure well-trained engineers. Solar plant condition: Solar plant weather is usually high and not suitable for work. The data generated by the solar system is context sensitive and can be affected by external factors such as weather conditions, solar radiation, bird droppings, and dust.

IV. CONCLUSION

This paper introduced the general architecture of the solar system and solar system surveillance systems, solar system problems, solar system surveillance techniques, and research trends. In this paper, we also introduced various pre-monitoring methods. By using these techniques, you can improve the performance of your photovoltaic system. Discuss the cost-effective photovoltaic monitoring system to monitor the electrical and environmental parameters of your photovoltaic array. An internet of things -based monitoring system for remote monitoring of photovoltaic systems. This technique can also speed up data transfer and store data on the server. Also exceed data at any time by connecting your mobile phone or laptop to the server. These cheap and efficient ones are very useful for residential applications. Reduce the overall cost of monitoring. Microcontrollers are commonly used in inexpensive and efficient surveillance systems. The artificial neural network method is used for precision systems. It takes less time and is more accurate than other advanced methods. Monitoring requires programming. It is also a good concept for assessing the performance and quality of the energy produced by photovoltaic systems. This review will help you0 develop new systems for remote solar system monitoring systems.

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