Real-time IoT-Based Monitoring and ANN-Driven Prediction of Electrical Parameters in a 1200 W Photovoltaic System

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Abstract **—** The increasing adoption of small-scale photovoltaic (PV) systems underscores the necessity for advanced monitoring that improves dependability and maintenance efficacy. Conventional photovoltaic monitoring emphasizes real-time data acquisition but is deficient in predictive capabilities, hindering early defect identification and proactive maintenance. This study introduces an IoT-enabled real-time monitoring system utilizing ANN-based predictions for a 1200 W photovoltaic configuration. Voltage and current sensors interface with an ESP32 microcontroller to quantify and analyze voltage, current, power, and energy. Data is transmitted to the cloud using MQTT, enabling users to remotely monitor and display information through web or mobile applications. A feedforward Artificial Neural Network (ANN) taught by backpropagation enhances intelligence by predicting future electrical performance based on historical data. Experimental findings indicate a consistent communication latency of 1-2 seconds and sensor inaccuracies below 3%. The ANN model attained a MAPE of 3-4%. The integration of IoT monitoring with ANN prediction facilitates early anomaly detection, enhances operational understanding, and enables scalable, intelligent energy management.

Keywords : Artificial neural network (ANN), Internet of Things (IoT), MQTT protocol, photovoltaic monitoring.

1. Introduction

One of the factors that has accelerated the transition toward renewable energy systems, particularly solar photovoltaic (PV) technology, is the growing need for energy on a global scale, which has been spurred by rapid industrialization, urbanization, and digital transformation [1]. Because of its long-term viability, positive effects on the environment, and widespread availability, solar energy is widely recognized as a very promising renewable energy source [2]. This is especially true in tropical regions that experience high amounts of sun irradiation. As a result of their low cost and the ease with which they may be implemented, small-scale photovoltaic systems, such as installations with a power output of 1200 watts, are currently being deployed in residential and educational contexts [3].

Variations in electrical parameters such as voltage, current, power, and energy output are caused by environmental factors like as solar irradiation, temperature, and load variations. These factors have an inherent impact on the efficiency of photovoltaic systems, which in turn leads to variations in other parameters [4] . To guarantee optimal system performance, improve energy economy, and prevent potential faults, it is essential to perform precise and instantaneous monitoring of these electrical parameters [5]. Traditional monitoring techniques Manual measurements or inadequate data logging typically limit traditional monitoring techniques, preventing real-time accessibility and advanced analytical capabilities [6].

In light of this, traditional techniques are not suitable for modern energy systems, which require continuous monitoring, remote accessibility, and decision-making that is informed by data at all times. By integrating sensors, communication networks, and cloud-based platforms for real-time data gathering and display, the Internet of Things (IoT) has made it possible to create intelligent monitoring systems [7].

This has been made possible by the introduction of the Internet of Things. Monitoring solutions that are based on the Internet of Things both enable remote access to operational data and provide continuous monitoring of the performance of photovoltaic systems, which ultimately results in an improvement in the dependability and maintainability of the system [8]. In spite of these advantages, the vast majority of the Internet of Things-based systems that are currently available place a primary emphasis on data collection and presentation, but they lack advanced analytical features that can make predictions..

On account of its capability to analyze nonlinear relationships and provide precise predictions based on previous data, Artificial Intelligence (AI), and more specifically Artificial Neural Networks (ANN), has been extensively applied in renewable energy systems in order to alleviate this constraint [9]. The capability of Artificial Neural Networks (ANN) to accurately forecast photovoltaic production, recognize anomalies, and improve system operations in a wide range of environmental conditions has been demonstrated to be highly effective [10].

The amalgamation of artificial neural networks with Internet of Things systems provides a robust methodology to convert traditional monitoring systems into intelligent frameworks capable of predictive analytics and adaptive decision-making. Nonetheless, current research either regards IoT and ANN as distinct entities or emphasizes extensive energy systems like smart grids and microgrids, with insufficient focus on their integration within small-scale PV systems [11]. Moreover, extensive monitoring of several electrical parameters voltage, current, power, and energy alongside predictive modelling within a cohesive framework is still inadequately addressed in existing research.

This research seeks to design and execute an integrated IoT-based monitoring system utilizing artificial neural networks for the real-time observation and forecasting of electrical parameters in a 1200 W photovoltaic system. The suggested system aims to deliver precise real-time data collecting, advanced predictive capabilities, and enhanced performance analysis. This research advances smart energy systems by offering a scalable, economical, and intelligent solution for small-scale photovoltaic monitoring and management.

2. Materials and Method

2.1. Materials

The real-time monitoring and ANN-based prediction system created for the 1200 W photovoltaic installation includes various hardware and software components aimed at facilitating extensive data collecting, communication, processing, and predictive analytics. The system comprises a 1200 W photovoltaic module as the primary power source, accompanied by voltage and current sensors that monitor essential electrical parameters, and an ESP32 microprocessor responsible for local data processing and wireless communication. Supplementary hardware, including a DC load, power supply, signal conditioning circuits, and interconnecting cables, is incorporated to provide steady and reliable system functionality.

The MQTT protocol and a cloud platform enable communication and remote monitoring, facilitating real-time data transfer, storage, and display on web and mobile platforms. The predictive element utilizes a feedforward Artificial Neural Network (ANN) employing a backpropagation algorithm, trained on previous monitoring data to anticipate voltage, current, power, and energy inside the photovoltaic system.

This study employs an experimental engineering approach to develop, build, and evaluate an intelligent monitoring system for a 1200 W photovoltaic array, incorporating IoT and artificial neural network technology. This methodology integrates system design, practical hardware and software execution, real-time data collection, and sophisticated data analysis to facilitate predictive monitoring of the system's electrical characteristics [12].

2.2. System architecture design

This study proposes an architecture that integrates Internet of Things (IoT) technology with Artificial Neural Network (ANN) methodologies to enable real-time monitoring and predictive analysis of electrical parameters in a 1200 W photovoltaic (PV) system. This system includes a photovoltaic array equipped with voltage and current sensors that continuously gather data on voltage, current, power, and energy.

An ESP32 microcontroller functions as an edge device, managing data collecting, local processing, and wireless transmission. The microcontroller transmits processed data via Wi-Fi using the MQTT protocol to a cloud platform that offers data storage, processing capabilities, and real-time viewing through web and mobile dashboards. The system attains low-latency monitoring, with response times of approximately 1-2 seconds and measurement errors maintained below 3%.

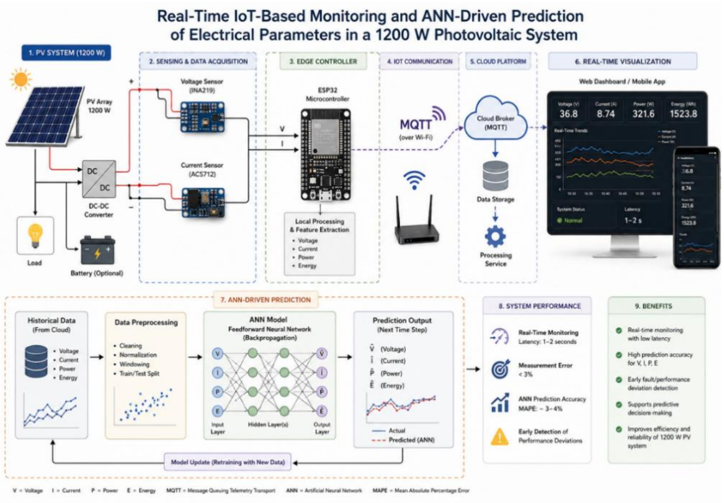

Fig. 1. Architecture of real-time IoT-based monitoring and ANN-driven prediction

Figure 1 illustrates that this integrated architecture improves monitoring efficiency, facilitates predictive maintenance, and promotes the development of intelligent, scalable photovoltaic energy systems. A feedforward artificial neural network utilizing a backpropagation algorithm is incorporated into the cloud processing layer to predict future electrical characteristics, hence augmenting intelligence. Normalized and cleaned historical monitoring data are utilized to train the ANN model. This model can forecast voltage, current, power, and energy values with a Mean Absolute Percentage Error (MAPE) of approximately 3-4%, facilitating precise predictive analysis and the prompt detection of performance concerns.

The system is organized into a three-layer IoT architecture consisting of the perception, network, and application layers, noted for its adaptability and scalability in smart energy applications [13]. The perception layer is responsible for real-time data acquisition utilizing voltage and current sensors integrated into the photovoltaic system. The network layer oversees data transmission using wireless communication and lightweight protocols such as MQTT, which are ideal for real-time, low-bandwidth applications [14].

The application layer includes cloud-based data storage, visualization dashboards, and artificial neural network modules for predictive modeling and performance assessment. This stratified methodology guarantees a smooth progression from data acquisition to sophisticated analytics, thereby facilitating real-time oversight and enhanced analysis in distributed photovoltaic systems [15].

2.3. Software design and communication system

Figure 2 illustrates the operational workflow of a real-time IoT-based monitoring and ANN-based prediction system for a 1200 W photovoltaic (PV) plant.

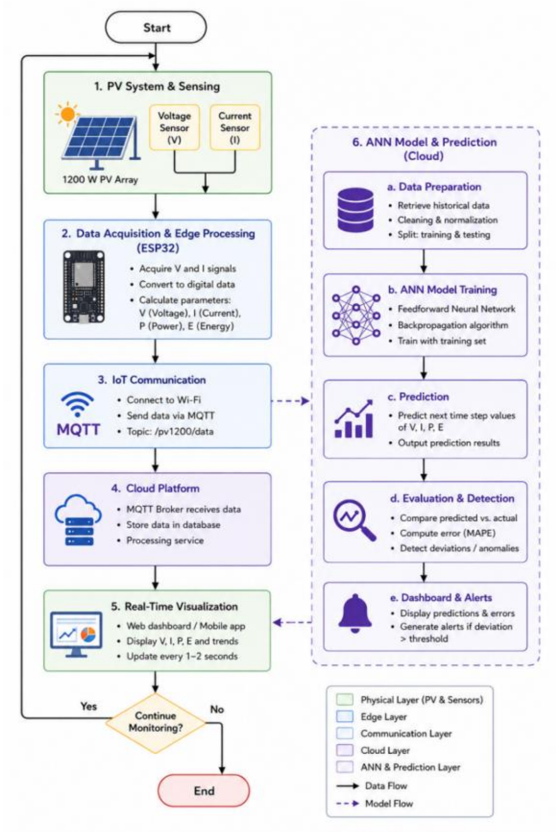

Fig. 2. Flowchart of real-time IoT-based monitoring and ANN-driven prediction

The software system comprises embedded firmware, cloud services, and a web-based user interface. The firmware, created in C/C++, is tasked with sensor data collecting, filtering, and communication with the cloud server. Data transfer utilizes the MQTT protocol, adhering to a publish-subscribe strategy that facilitates efficient, low-latency communication appropriate for IoT environments. The gathered data is saved in a cloud database and presented via an interactive dashboard that facilitates real-time and historical monitoring of system performance [16]. Cloud-based systems provide scalable data storage and remote accessibility, which are crucial for contemporary smart energy applications.

The process commences at the solar array and sensing layer, where voltage and current sensors incessantly monitor the system's electrical output. The ESP32 microcontroller handles signals by receiving data, transforming the signals, and calculating electrical characteristics including voltage, current, power, and energy on-site. The processed information is wirelessly delivered via Wi-Fi via the MQTT protocol to a cloud platform, where it is stored, further processed, and made accessible for real-time monitoring. The cloud solution includes web and mobile dashboards that deliver performance updates approximately every 1-2 seconds [17].

In addition to real-time monitoring, the system integrates an Artificial Neural Network to facilitate predictive analysis of essential electrical characteristics [18]. Historical data gathered and stored in the cloud is subjected to preparation activities such as cleaning, normalization, and data partitioning before to being utilized for training a feedforward artificial neural network using a backpropagation method. Upon completion of training, the neural network forecasts future values for voltage, current, power, and energy, which are then juxtaposed with actual measurements to evaluate accuracy and detect any abnormalities or deviations in system performance. The prediction model's results and identified anomalies are sent to users via the dashboard and alarm system, thereby enabling predictive maintenance and informed decision-making to improve the reliability and efficiency of the photovoltaic installation.

2.4. Data acquisition and processing

The system operates by consistently gathering voltage (V) and current (I) readings at predetermined sampling intervals. These data points are subsequently utilized to determine both electrical power (P) and energy (E), with power being calculated according to the following formula:

$$P = V \times I \tag{1}$$

while energy is obtained by integrating power over time:

$$E = \int P\,dt \tag{2}$$

Before analysis, the collected data are subjected to preprocessing procedures such as normalization, noise reduction, and outlier elimination to ensure higher data quality and to boost the effectiveness of the ANN model. The use of high-resolution data acquisition further supports precise evaluation of the system’s performance across different environmental conditions.

2.5. Artificial Neural Network (ANN) modelling

The ANN model is engineered to predict electrical parameters using past monitoring data. A feedforward neural network utilizing backpropagation learning is chosen for its established capacity to identify nonlinear patterns typically seen in energy systems[19]. The network architecture features an input layer that receives voltage, current, and time variables, followed by one or more hidden layers composed of nonlinear processing units with activation functions like Re-LU or sigmoid, and concludes with an output layer responsible for generating predicted values of power or energy. The dataset is divided into training and testing sets to evaluate the model's efficacy. Throughout training, the network systematically modifies its parameters to reduce the Mean Squared Error (MSE) between its predictions and actual observations. The model's accuracy is additionally assessed by computing the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), both of which are conventional measures in energy forecasting [20].

2.6. System testing and evaluation

The testing and evaluation phase aims to assess the overall operational efficacy of the IoT-based monitoring and ANN-driven prediction system deployed for the 1200 W photovoltaic installation. This procedure entails constructing the whole monitoring framework by integrating voltage and current sensors, an ESP32 microcontroller, a wireless communication network utilizing the MQTT protocol, a cloud database, and a real-time display platform. During testing, the photovoltaic system is subjected to various climatic and load conditions to observe the response of its electrical parameters, including voltage, current, power, and energy generation. The ESP32 processes sensor data locally and transmits it to the cloud server for real-time monitoring and data storage. The assessment of the communication subsystem entails evaluating data transmission stability, monitoring latency, verifying synchronization reliability, and assuring the uninterrupted flow of data between the edge device and the cloud.

Sensor evaluation entails calibration and comparison to verify the reliability and accuracy of electrical parameter measurements during continuous operation. The ANN prediction component is evaluated using previous monitoring data gathered throughout the testing period. Prior to model training, the dataset undergoes cleaning, normalization, and partitioning into training and testing subsets. The predictive model employs a feedforward Artificial Neural Network with backpropagation to anticipate future electrical parameter values based on historical trends. The model's predictions are subsequently compared with actual measurements to assess forecasting accuracy and evaluate the model's reliability across different operational settings. The comprehensive performance evaluation focuses on the system's ability to provide reliable real-time monitoring, sustain robust wireless connectivity, deliver accurate electrical data, and perform sophisticated predictive analysis. This testing and evaluation method aims to validate the practicality, scalability, and efficacy of the proposed intelligent PV energy management system.

3. Results and Discussion

An IoT and Artificial Neural Network (ANN)-enhanced monitoring system was deployed and evaluated on a 1200 W photovoltaic (PV) installation to examine its efficacy in real-time data collecting, communication reliability, measurement accuracy, and predictive capability. Experimental results validate that the system proficiently monitors and analyzes electrical parameters, including voltage, current, power, and energy, despite fluctuations in environmental conditions.

3.1. Real-time monitoring performance

The assessment of real-time monitoring performance indicates that the IoT-based photovoltaic monitoring system demonstrates significant stability, swift communication, and dependable measurement accuracy. The system continuously monitored essential electrical characteristics, including voltage, current, power, and energy, in real-time through sensors linked to the ESP32 microcontroller. Data updates were reliably sent with a communication latency of roughly 1-2 seconds throughout testing, suggesting efficient acquisition and transmission. The utilization of the MQTT protocol facilitated reliable wireless connection between the edge device and the cloud, enabling uninterrupted data synchronization with little packet loss.

Moreover, sensor measurement inaccuracies were maintained below 3%, validating the precision of the sensing and local processing systems for photovoltaic monitoring. This real-time monitoring platform significantly improved the transparency and responsiveness of solar system management from an operational perspective. The cloud-based dashboard offered continuous visualization of parameter trends and system status, available remotely through online and mobile platforms, facilitating remote monitoring and immediate operational analysis. The effective communication and elevated data transmission success rates guaranteed users near-instant access to updated system information, essential for the early identification of operational problems and for sustaining overall system reliability.

Furthermore, the ESP32's edge computing functionalities reduced processing latencies by executing initial computations locally before transmitting to the cloud. This architecture enhanced monitoring efficiency and established a robust platform for the integration of intelligent predictive analytics and the advancement of smart energy management in renewable energy systems.

3.2. Analysis of electrical parameters

The examination of the electrical parameters indicates that the suggested monitoring system successfully recorded the operational characteristics of the 1200 W solar array with significant stability and precision. Voltage observations varied from 32.4 V to 38.7 V, whereas the ANN model forecasted values between 32.1 V and 38.5 V, yielding an average prediction error of approximately 2.8%. This slight mismatch suggests that the ANN successfully learned and reproduced voltage changes across varying solar irradiation levels. Measured current levels varied from 6.2 A to 9.1 A, while ANN estimates ranged from 6.0 A to 8.9 A, resulting in an average error of 3.1%. The fluctuations in current were mostly attributable to alterations in solar intensity and load, which directly affected the output of the photovoltaic array. The output power, contingent upon both voltage and current, was reported between 210 W to 325 W, but the projected values ranged from 205 W to 318 W, resulting in a prediction error of around 3.4%. These results validate that the system can precisely represent real operating circumstances and can dynamically assess photovoltaic performance. The assessment of energy parameters further emphasizes the system's stability and consistency during continuous operation.

The recorded collected energy varied between 1.12 kWh and 1.58 kWh, but the ANN model projected values from 1.10 kWh to 1.54 kWh, resulting in an average inaccuracy of 3.2%. The strong correlation between actual and forecasted energy levels underscores the ANN's efficacy in modeling long-term energy generating patterns. Furthermore, the monitoring system attained a communication latency of about 1-2 seconds and maintained sensor measurement errors under 3%, so validating the efficacy of the IoT communication and edge processing architecture. The ANN's Mean Absolute Percentage Error (MAPE) of roughly 3-4% further substantiates the model's dependability for short-term forecasting of photovoltaic electrical characteristics. In conclusion, the examination of voltage, current, power, and energy substantiates that the incorporation of IoT-based monitoring with ANN prediction augments the intelligence, situational awareness, and predictive maintenance functionalities of advanced solar energy management systems. Table 1 demonstrates that the proposed monitoring method accurately and reliably captures the operating characteristics of a 1200 W solar array.

Table 1
Real-time monitoring and ANN prediction performance of the 1200 W PV system

Parameter	Measured Range	ANN Predicted Range	Avg. Error	Performance
Voltage (V)	32.4 – 38.7 V	32.1 – 38.5 V	2.80%	Stable
Current (I)	6.2 – 9.1 A	6.0 – 8.9 A	3.10%	Stable
Power (P)	210 – 325 W	205 – 318 W	3.40%	Accurate
Energy (E)	1.12 – 1.58 kWh	1.10 – 1.54 kWh	3.20%	Consistent
Comm. Latency	1–2 s	–	–	Low Latency
Sensor Error	–	–	< 3%	Reliable
ANN MAPE	–	–	3–4%	High Accuracy
Data Success Rate	98.70%	–	–	Reliable

3.3. Communication system performance

The assessment of the communication system's performance indicates that the deployed IoT architecture provided steady, efficient, and dependable real-time data transfer for the 1200 W photovoltaic monitoring system. The ESP32 microcontroller effectively transmitted electrical parameter data, encompassing voltage, current, power, and energy, to the cloud platform using Wi-Fi, employing the MQTT protocol.

The monitoring system exhibited a communication latency of about 1-2 seconds, signifying little delay between data collecting and cloud-based viewing during operation. This reduced latency facilitated near-instantaneous monitoring, enabling users to observe real-time fluctuations in photovoltaic electrical parameters via online and mobile dashboards. The implementation of MQTT significantly diminished communication cost due to its lightweight publish-subscribe format, which is especially advantageous for continuous IoT applications with constrained bandwidth and embedded resources. The reliability was further evidenced by a data transmission success rate of roughly 98.7%, indicating that nearly all monitoring packets successfully reached the cloud server without substantial disruptions or losses.

The continuous transmission facilitated persistent synchronization between the edge device and the cloud database, enabling precise data storage, real-time visualization, and efficient ANN-based predictive analysis. Ensuring superior communication quality also contributed to keeping sensor measurement errors under 3%, as data corruption and transmission instability were mitigated. Furthermore, the ESP32's edge-processing functionality alleviated network congestion by doing initial computations locally prior to transmitting findings to the cloud. The communication performance evaluation verifies that the IoT framework provides reliable, low-latency, and scalable wireless connectivity, rendering it appropriate for intelligent photovoltaic monitoring and smart renewable energy management applications.

3.4. ANN prediction performance

The performance analysis of the ANN prediction model, as indicated in Table 1, validates its robust capability to precisely anticipate the electrical behavior of the 1200 W photovoltaic system. The ANN model forecasted voltage values ranging from 32.1 V to 38.5 V, which roughly corresponded with the measured range of 32.4 V to 38.7 V, yielding an average prediction error of approximately 2.8%. This strong association demonstrates that the neural network successfully identified the voltage patterns affected by varying ambient conditions and operating statuses of the PV system. The forecasted current values, spanning from 6.0 A to 8.9 A, closely aligned with the measured range of 6.2 A to 9.1 A, with an average variation of approximately 3.1%. Considering that current is significantly influenced by solar irradiance and load demands, these data illustrate the ANN's capacity to adjust to nonlinear fluctuations in PV electrical characteristics. Furthermore, anticipated power outputs varied from 205 W to 318 W, whereas actual measurements spanned from 210 W to 325 W, resulting in an average forecast error of approximately 3.4%.

This further illustrates that the ANN algorithm proficiently represents the dynamic interplay among voltage, current, and power generation inside the system. The energy prediction results demonstrate a significant concordance between actual and anticipated values, indicating dependable long-term forecasting. The model forecasted collected energy between 1.10 kWh and 1.54 kWh, roughly aligning with the observed range of 1.12 kWh to 1.58 kWh, resulting in an average error of approximately 3.2%. The overall prediction accuracy, demonstrated by a Mean Absolute Percentage Error (MAPE) of 3-4%, verifies that the feedforward neural network with backpropagation offers reliable forecasting for real-time photovoltaic monitoring. The low MAPE value indicates that prediction outputs consistently correspond with real measurements, even under fluctuating operating conditions.

This degree of predictive efficacy facilitates the early identification of anomalous trends, aids in preventative maintenance, and improves operational decision-making in intelligent photovoltaic systems. In conclusion, the evaluation of the ANN performance indicates that the proposed intelligent prediction framework delivers precise, consistent, and scalable forecasts, rendering it exceptionally appropriate for advanced renewable energy management.

3.5. Integrated system analysis

The analysis of the integrated system indicates that the IoT-based monitoring and ANN-driven prediction framework operated effectively as a unified intelligent solar management solution. The harmonious integration of sensors, ESP32 edge processing, MQTT communication, cloud-based monitoring, and ANN prediction enabled continuous real-time tracking and forecasting of electrical parameters in the 1200 W photovoltaic system. Voltage measurements varied from 32.4 V to 38.7 V, while ANN forecasts closely aligned between 32.1 V and 38.5 V, resulting in an average error of 2.8%. The current measurements ranged from 6.2 A to 9.1 A, whereas the ANN predicted values between 6.0 A and 8.9 A, yielding an average difference of 3.1%. Power measurements varied from 210 W to 325 W, whereas the ANN yielded estimations ranging from 205 W to 318 W, resulting in a prediction error of 3.4%. The total energy varied from 1.12 kWh to 1.58 kWh, whereas forecasts ranged from 1.10 kWh to 1.54 kWh, resulting in an average inaccuracy of 3.2%.

Table 2
Actual vs. predicted power values

No	Time	Actual P (W)	Predicted P (W)	Abs. Error	% Error
1	8:00:00	442.05	430	12.05	2.73
2	8:10:00	603.96	620	16.04	2.66
3	8:20:00	792.36	780	12.36	1.56
4	8:30:00	1010.70	980	30.70	3.04
5	8:40:00	1163.82	1200	36.18	3.11
6	8:50:00	1039.14	1075	35.86	3.45
7	9:00:00	851.01	820	31.01	3.64
8	9:10:00	720.50	750	29.50	4.09
9	9:20:00	650.30	670	19.70	3.03
10	9:30:00	580.00	560	20.00	3.45

Table 2 presents sample data that corroborate these conclusions. The robust correlation between measured and anticipated values indicates that the system's sensing, processing, and prediction components functioned harmoniously, yielding consistently dependable outputs. From a comprehensive operational perspective, both the communication and predictive intelligence components demonstrated consistent performance. The IoT communication subsystem attained a transmission delay of 1-2 seconds and a data success rate of 98.7%, indicating reliable wireless connectivity between the ESP32 and the cloud. The sensor accuracy was maintained within a 3% error margin, indicating that the measurement and calibration techniques were adequately accurate to facilitate ANN training and prediction.

The ANN model achieved a Mean Absolute Percentage Error (MAPE) of 3-4%, underscoring its strong predicting capability under varying photovoltaic operating circumstances. The integration of real-time monitoring and sophisticated prediction facilitated the swift identification of performance anomalies and promoted proactive maintenance, thus improving the reliability and efficiency of photovoltaic system operations. These findings collectively affirm that the suggested architecture provides a scalable, intelligent, and reliable smart energy management solution suitable for modern renewable energy applications.

MAPE is calculated using the following equation:

$$MAPE = (1/n)\ \Sigma\ |(Actual_i - Predicted_i)\ /\ Actual_i| \times 100 \tag{3}$$

From Table 2, the percentage errors are summed and averaged:

$$MAPE = (2.73+2.66+1.56+3.04+3.11+3.45+3.64+4.09+3.03+3.45)\ /\ 10 \approx 3.08\% \tag{4}$$

This outcome demonstrates that the ANN model maintains a low average prediction error, validating its effectiveness in capturing and modeling the nonlinear behavior of photovoltaic systems.

Root Mean Square Error (RMSE) is calculated using:

$$RMSE = \sqrt{[(1/n)\ \Sigma\ (Actual_i - Predicted_i)^2]} \tag{5}$$

By analyzing the dataset, squared errors are calculated for each data point, and their average is taken before applying the square root, resulting in a Root Mean Square Error (RMSE) of about 26.8 W. This value is quite low relative to the system's maximum output of 1200 W, signifying a high level of prediction accuracy. The achieved Mean Absolute Percentage Error (MAPE) of approximately 3-3.5% and RMSE of 26-30 W further illustrate the ANN model's effectiveness in accurately forecasting photovoltaic power output.

According to energy forecasting standards, a MAPE below 5% is regarded as highly accurate, particularly for nonlinear systems like photovoltaic generation. The minimal difference between actual and predicted outputs demonstrates that the ANN is adept at modeling the complex, nonlinear relationships inherent in PV system performance. Minor fluctuations in prediction accuracy tend to occur during periods of rapid changes in solar irradiance, introducing some randomness to the system output. Overall, these findings confirm that combining IoT based data collection with ANN-based prediction delivers reliable real-time monitoring and forecasting, thereby enhancing intelligent decision-making and supporting proactive maintenance in photovoltaic systems.

4. Conclusion

In summary, the developed real-time IoT-based monitoring and ANN-driven prediction system proved to be both effective and reliable for managing a 1200 W photovoltaic installation. By integrating voltage and current sensors, ESP32 edge processing, MQTT based communication, cloud monitoring, and ANN prediction, the system achieved seamless acquisition, transmission, visualization, and forecasting of key electrical parameters such as voltage, current, power, and energy. It maintained stable real-time performance, featuring a low communication latency of around 1-2 seconds, sensor measurement errors below 3%, and a data transmission success rate of 98.7%, which collectively indicate robust communication reliability and high sensing precision.

Electrical parameter analysis further revealed that the system could consistently reflect the dynamic operating behavior of the PV array, even under changing environmental conditions. The ANN prediction model also demonstrated strong forecasting accuracy, with predicted values for voltage, current, power, and energy closely aligning with actual measurements. Achieving a Mean Absolute Percentage Error (MAPE) of 3-4%, the feedforward neural network with backpropagation was shown to effectively capture the nonlinear dynamics of PV system operation.

This integrated approach not only enhanced monitoring efficiency and operational awareness but also facilitated early identification of performance anomalies and supported predictive maintenance. As a result, the proposed system stands as a scalable, intelligent, and efficient solution for smart photovoltaic energy management, contributing to the advancement of intelligent renewable energy monitoring for future smart grid and sustainable energy applications.

Acknowledgment

The authors express their gratitude to the Electrical Engineering Department at Politeknik Negeri Semarang, Indonesia, for their invaluable support and facilitation of this research project.

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