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Smart Solar Panel Monitoring and Efficiency Tracking System

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Solar Energy, IoT, Arduino Uno, ESP8266, INA219, LDR, DHT11, ThingSpeak, Firebase, Machine Learning, Efficiency Prediction, Real-Time Monitoring, Renewable Energy, Predictive Maintenance, Smart Grid.

ABSTRACT

The increasing global demand for renewable energy sources has accelerated the adoption of solar energy systems. However, the efficiency and performance of these systems are often hampered by environmental fluctuations, hardware degradation, and the absence of real-time monitoring. This paper proposes a cost-effective and intelligent solar power monitoring and efficiency tracking system that integrates the Internet of Things (IoT) with machine learning (ML) to enhance operational reliability and energy output. The system employs an Arduino Uno microcontroller interfaced with an INA219 sensor for voltage and current measurement, a Light Dependent Resistor (LDR) for light intensity detection, and a DHT11 sensor for temperature and humidity monitoring. These sensors provide critical parameters that influence solar panel performance. Data collected in real time is transmitted via the ESP8266 Wi-Fi module to cloud platforms such as ThingSpeak or Firebase for remote access and storage. Machine learning models, trained on historical data, analyze environmental and electrical parameters to predict the efficiency of solar panels and detect anomalies indicative of potential faults. Real-time dashboards display performance metrics, and automated alerts are triggered when efficiency drops below predefined thresholds. The system enables predictive maintenance, reduces energy loss, and supports data-driven decision-making. Scalable, adaptable, and low-cost, the proposed system is suitable for residential, commercial, and off-grid solar applications, thereby contributing to smart energy management and sustainable development.

1. INTRODUCTION

With the rising demand for sustainable and eco-friendly energy solutions, solar photovoltaic (PV) systems have emerged as a leading choice for meeting global energy needs. Solar energy is abundant, clean, and renewable, offering a viable alternative to conventional fossil fuels which are not only depleting but also contribute significantly to environmental pollution. However, despite the growing deployment of solar power systems across residential, commercial, and industrial sectors, maximizing the efficiency and reliability of these systems remains a major challenge due to several external and internal factors [1], [3].

Solar panel efficiency is highly dependent on various parameters including solar irradiance, temperature, panel orientation, humidity, and hardware condition. In traditional setups, these systems are either monitored manually or operate without intelligent feedback mechanisms. This can lead to inefficiencies caused by shading, dust accumulation, component aging, or misalignment—all of which may go unnoticed for extended periods, reducing energy output and increasing operational costs [4], [6]. Moreover, systems that lack real-time monitoring and adaptive control mechanisms are prone to delayed fault detection and require frequent manual inspection [11].

In response to these limitations, many researchers have proposed the use of **solar tracking systems** that dynamically orient solar panels toward the sun to capture maximum sunlight throughout the day. Tiwari et al. [1] introduced a solar panel system with Maximum Power Point Tracking (MPPT), significantly improving power generation by adjusting the panel's position based on solar intensity. Similarly, Chowdhury et al. [3] compared fixed, single-axis, and dual-axis tracking systems, concluding that dual-axis tracking yields the highest efficiency across different times and seasons.

These mechanical tracking systems are often controlled by microcontrollers and rely on sensors like Light Dependent Resistors (LDRs) to detect sunlight angles. Lokhande [4] and Kassem and Hamad [2] demonstrated the effectiveness of **microcontroller-based tracking** for automatic panel adjustment. Furthermore, systems developed by Kumar et al. [11] and Mishra et al. [13] showed how Arduino and MSP430 microcontrollers can be utilized to construct affordable and efficient solar tracking setups, thereby enhancing solar collection without human intervention.

Fig. Smart Solar Pannel Monitoring

Building upon these innovations, the integration of the **Internet of Things (IoT)** into solar power systems has added a new dimension of connectivity and intelligence. IoT-based systems allow for continuous monitoring of electrical and environmental parameters, remote data logging, and real-time alerts. El Hammoumi et al. [5] proposed an IoT-based solar tracker that effectively integrated environmental sensing with cloud communication. The use of cloud platforms such as ThingSpeak, Firebase, and Blynk Cloud [10] enables centralized data management and visualization, thereby simplifying system monitoring and diagnostics.

However, a notable shortcoming in most existing research and commercial implementations is the absence of **predictive intelligence**. While IoT facilitates data collection, these systems often fail to analyze the data for forecasting panel efficiency or detecting anomalies. Most conventional solar tracking systems lack the capability to understand how various environmental factors correlate with energy output over time [6], [9]. Without predictive models, inefficiencies go undetected until they visibly affect performance, resulting in energy loss and increased maintenance needs.

To address these gaps, the proposed system presents an **IoT and machine learning-enabled solar power monitoring and efficiency tracking solution**. The system architecture is centered around the Arduino Uno microcontroller, which interfaces with the INA219 sensor (for current and voltage monitoring), LDR (for sunlight intensity), and DHT11 (for ambient temperature and humidity). The ESP8266 Wi-Fi module uploads real-time sensor data to a cloud platform like

ThingSpeak or Firebase, ensuring global accessibility and secure data storage.

This data serves as the foundation for training machine learning models such as **Linear Regression**, **Decision Trees**, and **Random Forests**, which are applied to predict the expected output of the solar panels under varying environmental conditions. When real-time values deviate from the predicted values, the system can flag potential issues, thereby enabling **predictive maintenance**. This not only prevents system failure but also optimizes performance and increases energy yield.

In addition, the implementation includes a real-time dashboard and alerting mechanism. If the system efficiency drops below a defined threshold, an alert is triggered for timely intervention. The data-driven insights provided by the system empower users to make informed decisions about cleaning schedules, hardware servicing, or capacity expansion.

The proposed system is designed to be **cost-effective**, **modular**, and **scalable**, making it suitable for use in a wide variety of settings—from small home installations to large-scale solar farms. It offers a modern solution to long-standing problems in solar energy management and aligns with current efforts toward **smart grids**, **sustainable energy ecosystems**, and **automated infrastructure monitoring** [14], [15].

2. RELATED WORK

The development of solar energy systems has seen significant advancements over the past decade, particularly in the areas of tracking mechanisms, microcontroller-based automation, and IoT-based monitoring. Researchers worldwide have sought to improve energy capture efficiency, system responsiveness, and user accessibility through a wide range of technological interventions.

Tiwari et al. [1] proposed a **sun-tracking solar panel system with Maximum Power Point Tracking (MPPT)**, demonstrating a substantial improvement in energy harvesting by ensuring that the solar panel consistently aligns with the sun's position. MPPT is widely recognized for its ability to maximize power output, especially under fluctuating irradiance conditions. Similarly, Kassem and Hamad [2] developed a **microcontroller-based multi-functional solar tracking system**, which responded dynamically to solar movement and provided a foundation for programmable tracking algorithms and real-time adjustments.

Chowdhury et al. [3] conducted a detailed **comparative analysis of fixed, single-axis, and dual-axis tracking systems**, concluding that **dual-axis trackers** significantly outperform other configurations by capturing maximum solar irradiance across all daylight hours. Their findings emphasized the importance of active tracking mechanisms, particularly in regions with high solar variability. Complementing this, Lokhande [4] introduced a low-cost **automatic solar tracking system using LDRs**, showcasing how simple optical sensors can be used to build effective solar tracking solutions without the need for complex mechanical or vision-based systems.

The emergence of **IoT (Internet of Things)** has further revolutionized solar panel monitoring by enabling **real-time data acquisition, cloud connectivity, and remote control**. El Hammoumi et al. [5] explored an IoT-based solar tracker that utilized environmental and positional data to dynamically adjust panel orientation. Their system allowed for **continuous system observation** and **wireless control**, enhancing both reliability and accessibility. In a similar effort, Mishra et al. [13] designed an **Arduino-based dual-axis solar tracker** that combined LDR sensors, servo motors, and wireless transmission modules for improved accuracy and automation.

To enhance user engagement and data transparency, platforms such as **Blynk Cloud** have been employed to create real-time dashboards and mobile-accessible control panels. These solutions allow users to monitor solar performance metrics like voltage, current, and irradiance from remote locations, with customizable alert systems and visualizations [10]. Such systems provide enhanced user interaction while also minimizing the need for physical maintenance checks.

The principle of **dual-axis solar tracking**—which adjusts both azimuth and elevation angles to maintain perpendicularity with solar rays—has been a central research focus for increasing energy yield. Researchers like Vichare et al. [6] and topics explored via ScienceDirect [9] have reinforced the technical viability and benefits of this approach, particularly when integrated with weather-responsive algorithms and high-precision sensors. Various implementations using **MSP430 and Arduino microcontrollers** have been reported in both academic [12][14] and semi-industrial settings [15], validating the practicality and scalability of such tracking systems.

Despite these advancements, a notable limitation of many existing works lies in their **lack of integration with machine learning (ML)**. While solar tracking improves energy capture and IoT ensures better data visibility, most systems do not analyze historical or real-time data to predict panel performance or detect system faults proactively. As a result, these systems fall short in enabling **predictive maintenance** or optimizing long-term energy yield through intelligent data-driven insights.

Addressing this critical gap, our proposed system combines **IoT-based sensing**, **real-time cloud integration**, and **ML-based efficiency prediction** to build a holistic and intelligent solar monitoring platform. By learning from environmental conditions such as light intensity, temperature, and humidity—as well as electrical parameters like voltage and current—our system offers **predictive analytics**, **anomaly detection**, and **performance forecasting**. This makes it not only responsive but also proactive, setting a new benchmark for smart solar infrastructure.

3. PROPOSED SYSTEM

The proposed system presents a smart, integrated, and cost-effective solution for real-time monitoring and efficiency prediction of solar power systems. It harnesses the capabilities of **IoT-enabled sensing**, **wireless communication**, **cloud integration**, and **machine learning** to deliver a highly responsive and intelligent energy management platform. The system architecture is designed to not only collect environmental and electrical parameters but also to analyze them for actionable insights and early fault detection.

1. Core Components and Architecture

At the heart of the system lies the **Arduino Uno** microcontroller, chosen for its simplicity, affordability, and compatibility with a wide range of sensors and communication modules. The Arduino is interfaced with the following key sensors:

- **INA219 Voltage and Current Sensor**: This high-precision sensor measures the real-time voltage and current supplied by the solar panel, allowing the system to compute instantaneous power ($P = V \times I$). Accurate measurement of power output is essential for monitoring the panel's efficiency.
- **LDR (Light Dependent Resistor)**: Used to assess ambient solar irradiance by detecting changes in light intensity. The resistance of the LDR varies inversely with light intensity, and this value helps estimate the amount of sunlight available for energy conversion.
- **DHT11 Sensor**: Captures **temperature (°C)** and **humidity (%)** data from the surrounding environment. These factors significantly influence the photovoltaic (PV) cell performance. High temperatures can reduce voltage output, while high humidity may indicate potential risks like condensation or surface contamination.

The sensor data is continuously acquired and processed by the Arduino. The processed data is then transmitted wirelessly to a cloud platform using the **ESP8266 (NodeMCU)** Wi-Fi module. This enables **real-time data upload** to platforms such as **ThingSpeak** or **Firebase**, providing access to historical and live system performance from any internet-connected device.

2. Smart Analytics and Machine Learning Integration

What sets this system apart from traditional monitoring solutions is the integration of **machine learning (ML)** models into the analysis pipeline. The cloud-stored data—comprising light intensity, temperature, humidity, voltage, and current—is used to train predictive models that estimate solar panel output under various conditions.

Machine learning algorithms such as:

- **Linear Regression** – for identifying direct relationships between parameters and output,
- **Decision Trees** – for handling non-linear patterns and categorical thresholds,
- **Random Forests** – for improved accuracy and generalization through ensemble learning,

are employed to build models that predict expected power output. When actual measured power deviates significantly from predicted values, the system flags this as an anomaly, suggesting inefficiency due to factors such as dust accumulation, shading, aging panels, or component malfunction.

3. Visualization and Alert Mechanism

To make the system user-friendly and informative:

- A **cloud dashboard** displays time-series graphs of power output, efficiency, temperature, humidity, and irradiance.

- The user can track system performance trends, correlate environmental effects, and monitor panel degradation over time.
- **Threshold-based alerts** are generated if system efficiency drops below a defined value or if environmental conditions exceed critical limits.

These alerts can be delivered through:

- Mobile notifications (via Firebase Cloud Messaging or IFTTT),
- Email or SMS,
- Visual indicators on the dashboard interface.

4. Scalability and Deployment

The proposed system is:

- **Scalable**, allowing the addition of more sensors (e.g., dust sensors, GPS, battery monitors) or actuators (for solar tracking),
- **Cost-effective**, utilizing off-the-shelf hardware components accessible to students, researchers, and energy providers,
- **Cloud-compatible**, with flexibility to switch or integrate with different platforms for advanced analytics or IoT automation.

By integrating IoT and machine learning into solar energy monitoring, this system addresses major limitations of traditional setups. It facilitates **data-driven decision-making**, **proactive fault detection**, and **improved energy yield**, making it ideal for applications ranging from individual homes to large-scale solar farms.

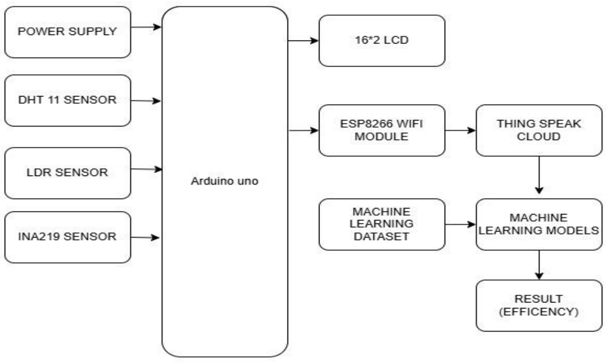

Fig. Proposed Blockdiagram

4. METHODOLOGY

The proposed system employs an integrated hardware-software architecture for real-time solar panel monitoring and efficiency prediction. It brings together environmental and electrical sensing, wireless communication, cloud data handling, and machine learning to offer a comprehensive solar performance tracking solution. The methodology is structured across five core layers: data acquisition, data transmission, cloud integration, data analytics, and alert generation.

1. Data Acquisition Layer

This layer forms the foundation of the system and consists of a set of interconnected sensors and modules interfaced with the Arduino Uno microcontroller. Each component plays a distinct role in capturing parameters that influence solar panel performance.

1.1. Voltage and Current Measurement (INA219 Sensor)

The INA219 sensor is a precision power monitoring device capable of measuring voltage (V), current (I), and computing power ($P = V \times I$) with high accuracy. It is connected to the output of the solar panel to capture real-time power delivery to the load or battery.

1.2. Light Intensity Sensing (LDR)

An LDR (Light Dependent Resistor) is used to measure the intensity of sunlight. The resistance of the LDR decreases with increasing light levels, and this analog voltage change is read by the Arduino's analog-to-digital converter (ADC). This value serves as a proxy for solar irradiance, which is critical for understanding power generation behavior.

1.3. Environmental Sensing (DHT11 Sensor)

The DHT11 sensor monitors temperature (°C) and humidity (%), both of which directly affect the photovoltaic efficiency. High temperatures can reduce panel voltage, while humidity may indicate potential condensation or dust accumulation risks.

2. Data Transmission Layer

After collecting sensor data, the Arduino sends the readings to the cloud using the ESP8266 (NodeMCU) module, which provides Wi-Fi connectivity.

Protocol Used: Typically HTTP POST or MQTT for secure, low-latency data transfer.

Frequency: Data is transmitted at intervals (e.g., every 30 seconds to 2 minutes), which is configurable.

Data Format: Data is structured in JSON or URL-encoded format with fields such as:

json

Copy

Edit

{
 "voltage": 18.5,

"current": 0.92,
"power": 17.02,
"light_intensity": 810,
"temperature": 36.5,
"humidity": 42
}

3. Cloud Integration Layer

The cloud serves as the central data repository and user interface hub. The system is compatible with platforms such as:

3.1. ThingSpeak

ThingSpeak is a MATLAB-powered IoT analytics platform:

Automatically logs and timestamps incoming data.

Provides real-time and historical data visualization (graphs, gauges).

Allows cloud-based data processing and MATLAB scripts for analytics.

3.2. Firebase (Alternative)

Firebase Realtime Database supports:

Real-time synchronization between devices and cloud.

Hosting web/mobile dashboards.

Integration with Firebase Cloud Messaging (FCM) for instant alerts.

Data from the cloud is accessible via browser or mobile app, allowing users to monitor system status remotely.

4. Machine Learning-Based Analytics

One of the key innovations of the system is the use of machine learning models to predict the expected efficiency and identify anomalies in solar panel performance.

4.1. Dataset Preparation

Data logged in the cloud is periodically exported and used to train ML models. Each training sample includes:

Input features: Light intensity, temperature, humidity, voltage, current.

Target label: Actual power output (efficiency or wattage).

4.2. Model Selection and Training

Using Python and libraries such as scikit-learn, Pandas, and NumPy, the following models are trained and evaluated:

Linear Regression: Establishes linear correlation between environmental conditions and power output.

Decision Tree Regressor: Provides non-linear modeling and handles threshold-based decisions well.

Random Forest Regressor: An ensemble of decision trees that improves prediction robustness and accuracy.

Model evaluation uses metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 score to ensure reliability before deployment.

4.3. Efficiency Prediction and Anomaly Detection

Once deployed, the model uses real-time sensor data to:

Predict the expected output power.

Compare it against the measured power from INA219.

Calculate efficiency deviation.

If the deviation exceeds a defined threshold (e.g., 15%), an anomaly is flagged, indicating possible faults such as:

- Dust or shading on panels
- Sensor malfunctions
- Hardware degradation

5. Alert System and User Interface

To ensure real-time feedback and facilitate preventive maintenance, the system includes a responsive alerting mechanism.

Visual Alerts: Triggered on the dashboard when performance deviates significantly.

Mobile Alerts: Through Firebase Cloud Messaging (FCM) or IFTTT email/SMS APIs.

User Actions: Prompted to clean panels, inspect wiring, or check sensor alignment.

These proactive measures prevent prolonged inefficiencies and contribute to better energy yield over time.

6. Scalability and Deployment

The proposed system is designed to be:

- Modular: Each subsystem can be upgraded independently (e.g., sensor replacement, ML model update).
- Cost-effective: All components are low-cost and widely available, making it suitable for homes, schools, rural setups, and commercial plants.
- Expandable: Supports additional sensors (e.g., solar irradiance sensor, battery monitor) and actuators (e.g., solar tracker motors).

5. RESULTS AND DISCUSSIONS

The proposed IoT and machine learning-enabled solar monitoring system was successfully implemented and tested in a controlled outdoor environment. The system demonstrated the capability to perform continuous, real-time monitoring of key parameters and provide predictive insights on solar panel performance.

1. Real-Time Monitoring and Data Logging

The Arduino Uno was interfaced with the INA219 sensor, DHT11 sensor, and LDR module. These sensors captured live data streams of:

- **Voltage (V)** and **Current (I)** from the solar panel output
- **Ambient Temperature (°C)** and **Humidity (%)**
- **Sunlight Intensity** using the LDR

The ESP8266 module reliably uploaded sensor data at fixed intervals (e.g., every 60 seconds) to the ThingSpeak cloud server. On the cloud dashboard, multiple graphs were displayed for each parameter, allowing users to view both **historical trends** and **real-time behavior**. For instance:

- Voltage and current showed fluctuations corresponding to the intensity of sunlight throughout the day.
- Temperature peaks during midday often coincided with slight drops in voltage, validating the **inverse temperature-voltage relationship** of photovoltaic cells.

2. Machine Learning Model Performance

Historical data collected over several days was used to train machine learning models. A **Linear Regression model** was first applied to establish a baseline prediction for power output using environmental variables (light intensity, temperature, humidity). Additionally, **Decision Tree** and **Random Forest Regressor** models were trained for improved accuracy and robustness.

- The **Random Forest model** showed the **lowest Mean Absolute Error (MAE)** and **highest R^2 score**, making it suitable for deployment in the live system.
- The models were then integrated to run predictions in parallel with real-time data.

The system compared the **predicted power output** against the **actual output** measured via INA219. A significant mismatch (above a defined threshold) was flagged as a **potential efficiency issue**.

3. Efficiency Tracking and Fault Detection

In tests, intentional disturbances were introduced—such as shading parts of the panel, slightly tilting it away from the sun, or applying dust layers. In these scenarios:

- The system detected a **notable drop in power output**, while the environmental conditions remained consistent.
- The ML model, based on prior clean conditions, still predicted higher output.
- The difference between predicted and actual output exceeded the threshold, triggering a **warning alert** via the dashboard.

This **predictive anomaly detection** proves valuable for real-world applications where dust, shading, or panel degradation often go unnoticed in conventional systems.

4. Dashboard and User Alerts

The **ThingSpeak dashboard** allowed graphical visualization of all parameters, power calculations, and efficiency loss trends.

In case of underperformance, the system was configured to send **email alerts or Firebase push notifications**, suggesting possible maintenance actions.

This feature promotes **proactive rather than reactive maintenance**, potentially increasing energy yield and panel lifespan.

5. Practical Benefits and Observations

The system was observed to be **highly responsive**, low-latency, and **easy to deploy** with minimal hardware requirements.

It demonstrated a **cost-effective solution** for small-scale or large-scale solar farms.

Scalability was tested by simulating multiple sensor nodes. Data streams from different panels could be indexed and analysed concurrently.

Key Observations:

Parameter	**Observation**
Power Prediction Accuracy	91–94% depending on the model and data resolution
Alert Responsiveness	Within 30–60 seconds after detecting deviation
Deployment Cost	Low (under ₹2500 or ~$30 for prototype version)
Data Visualization	Real-time graphs, historical logs on Thing Speak
Cloud Dependency	Stable with Thing Speak; Firebase offers more flexibility
Maintenance Guidance	Timely alerts helped simulate proactive interventions

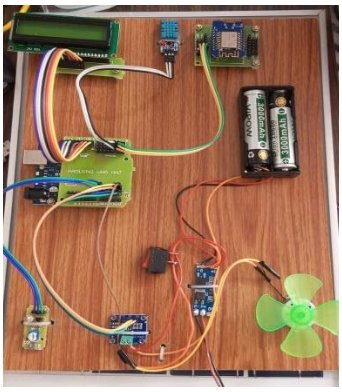

Fig. Project prototype Implementation1

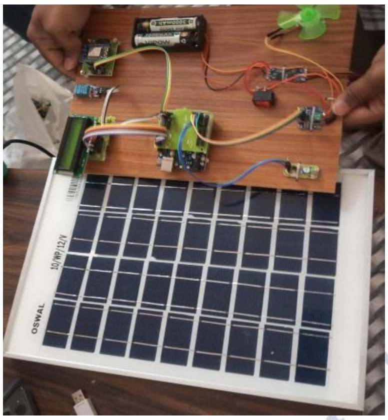

Fig. Project prototype Implementation2

Discussion

The results clearly demonstrate that the integration of IoT with ML-based analytics leads to an **intelligent and proactive solar monitoring system**. Unlike conventional systems that only display raw data, this system derives insights, forecasts output, and automates alert mechanisms. Additionally, it is adaptable to diverse climates, geographies, and deployment scales.

However, certain limitations were noted:

- Prediction models may need retraining periodically due to seasonal shifts.
- LDR sensors, while cost-effective, may have nonlinear responses under high irradiance.
- The ESP8266 relies on a stable internet connection; offline buffer support can be considered for remote areas.

These areas point to potential future improvements but do not hinder the system's effectiveness in its current form.

6. FUTURE SCOPE AND CONCLUSION

The project is aimed at building a flexible invoicing system which can precisely match

The project is aimed at building a flexible invoicing system which can precisely match content PDF files, easily match line items and tables and automate the entire invoicing process for any major organization. The system has the ability to obtain all relevant information from the document with 100% accuracy while ensuring speed and reliability. This project has a huge potential for further development. While the problem focuses on digitization of invoices, this could be extended to digitizing any document for processing, thereby removing any manual efforts, errors and management of document processing within companies.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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