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An IoT-Enabled, THD-Based Fault Detection and Predictive Maintenance Framework for Solar PV Systems in Harsh Climates: Integrating DFT and Machine Learning for Enhanced Performance and Resilience

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ABSTRACT

This research introduces an advanced energy management approach for PV setups situated in demanding semi-arid environments, specifically focusing on Baniwalid, Libya. Conventional energy management systems often depend on fixed parameters or basic models, which only address a limited scope of environmental variables. Such systems lack the adaptability to effectively respond to fluctuating conditions like intense heat, dust buildup, and intermittent shading, all of which can undermine solar panel performance. To overcome these limitations, the study incorporates artificial neural networks within an Internet of Things-based framework. This system utilizes a network of affordable sensors to collect real-time operational data from PV arrays. Via applying Discrete Fourier Transform techy, the system extracts key features such as Total Harmonic Distortion from electrical signals, which serve as early indicators of potential faults. Machine learning algorithms then leverage this data to forecast energy output as well as monitor the daily performance ratio, enabling the detection of gradual performance declines. During a ten-day observation period, the framework recorded a decrease in DPR from 97% to 93%, primarily attributed to temperature swings as well as dust accumulation on solar modules. The ANN-based model successfully correlated predicted outcomes with actual measurements, highlighting its potential for accurate system health assessment. The hybrid methodology combining physics-based signal analysis with data-driven intelligence facilitates proactive maintenance strategies that minimize unexpected interruptions, optimize energy yields, and can be efficiently deployed at the network edge. By transforming PV systems into adaptive, self-monitoring assets, this work enhances operational resilience under extreme conditions and offers a scalable solution that can be applied to smart energy management globally.

إطار عمل للكشف عن الأعطال والصيانة التنبؤية لأنظمة الطاقة الشمسية الكهروضوئية في المناخات القاسية، مدعوم بتقنية إنترنت الأشياء ومعتمد على تحليل التشوه التوافقي الكلي: دمج نظرية التصميم الوظيفي والتعلم الآلي لتحسين ومرونة الأداء

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الكلمات المفتاحية

نظام إدارة الطاقة
كشف الأعطال
تحويل فورييه السريعة
المراقبة الآنية
التعلم الآلي

الملخص

تلخص هذه الدراسة تطوير نظام ذكي لإدارة الطاقة يعتمد على إنترنت الأشياء والشبكات العصبية الاصطناعية لتحسين أداء أنظمة الطاقة الشمسية الكهروضوئية في البيئات القاسية مثل بني وليد في ليبيا. يواجه النظام الكهروضوئي تحديات بيئية مثل ارتفاع الحرارة وتراكم الغبار والتظليل الجزئي، والتي تؤثر سلبًا على الأداء ولا يمكن للأنظمة التقليدية التعامل معها بدقة بسبب اعتمادها على نماذج بسيطة. يعتمد النظام المقترح على دمج مستشعرات منخفضة التكلفة مع تحليل طيفي قائم على تحويل فورييه المنفصل لاستخراج مؤشرات التشوه التوافقي الكلي من موجات الجهد والتيار، مما يتيح الكشف المبكر والدقيق عن الأعطال. كما يستخدم نماذج تعلم آلي للتنبؤ بإنتاجية الطاقة وتقدير تدهور الأداء مع مرور الوقت. أظهرت النتائج التجريبية دقة عالية في التنبؤ بفضل تجاوز مؤشر R^2 قيمة 0.92 وانخفاض RMSE لأقل من 9.5، مع رصد انخفاض نسبة الأداء اليومي للألواح الشمسية من 97% إلى 93% خلال فترة المراقبة نتيجة العوامل البيئية. تكمن أهمية الدراسة في منهجيتها الهجينة التي تجمع بين تحليل الإشارات الفيزيائية والذكاء الاصطناعي، ما يسمح بالصيانة التنبؤية وتقليل فترات التوقف غير المخطط لها، وزيادة إنتاج الطاقة من خلال التدخلات في الوقت المناسب. يتيح النظام أيضًا بنية مرنة وقليلة التكلفة قابلة للتطوير والنشر على الحافة. بشكل عام، تساهم نتائج البحث في تعزيز استدامة وكفاءة البنية التحتية للطاقة الشمسية في البيئات الصعبة، وتقدم نموذجًا ذكيًا وقابلاً للتكرار عالميًا لإدارة الطاقة.

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Introduction

Driven by concerns about climate change and global warming, the global renewable capacity by the end of 2025, is expected to see massive growth, with projections suggesting solar PV alone will surpass 3,000 GW, contributing significantly to a total capacity projected to approach or exceed 6,000 GW, as annual additions are forecast to hit a record ~793 GW. This growth in the RE market reflects a global shift towards renewable and sustainable energy technologies [1].

The integration of Internet of Things (IoT) technology into Energy Management Systems (EMS) has significantly improved the daily performance ratio of Solar Panels [2]. Furthermore, EMSs based on the Internet of Things offer real-time monitoring and control requirements that enhance dependability and energy economy. This research also looks at the use of IoT technology for controlling and enhancing solar panel performance [3], addressing significant issues and providing a clear implementation process. The energy management sector has seen a lot of impact thanks to the evolvement of Internet of Things (IoT) technology [4]. How better can utilize energy than through smart technologies the introduction of IoT in energy systems has facilitated the development of innovative ways to optimize energy usage thereby enhancing the Daily Performance Ratio of renewable energy sources. Solar energy is one of the most important renewable energy sources. It is seen that solar energy has the potential to replace conventional energy sources in a sustainable and eco-friendly manner. The focus of this study was on IoT-based energy management technology to improve the solar panel output. To help with analyzing, decision-making, and data collection with real-time. The use of IoT will help monitor and optimize energy consumption, thus improving the overall Daily Performance Ratio of the solar panels. These systems may have collected data on various parameters such as solar irradiance, temperature, and orientation of the panel that subsequently adjust the operational parameters dynamically for better energy benefits [5,6]. IoT energy management systems guarantee no problems with the solar panels. It monitors everyday activities while also foreseeing faults to avoid larger troubles like breakage for max efficiency. Using machine learning in these systems can improve their abilities to predict things better and intervene faster [7]. Recent studies have determined the Daily Performance Ratio of IoT in improving the performance of solar energy systems [8]. For example, [9] study elucidated the significance of IoT for real-time monitoring and control of solar panels that, as a result, augment Daily Performance Ratio of Working Energy significantly. Likewise, studies by [2-5] said that the IoT-enabled energy management systems successfully reduce operational costs and improve energy outcome. Using IoT in solar energy solutions doesn't only support global sustainability of energy solutions such as solar, but it also helps in addressing the challenges faced in energy management in the remote, off-the-grid locations. Thanks to improvements in the IoT Technology, it is possible to create more resilient and adaptive energy infrastructures capable of operating under some environmental conditions and energy demands [9]. The aim of this research is to IoT based energy management techniques for optimum solar power generation. The analysis of literature to identify best practices and provide innovative solutions to maximize the daily performance ratio and reliability of solar energy systems will be shown in case study.

Materials and Methods

Experimental location and deployment environment

The experimental study was done at a personal solar photovoltaic (PV) installation site which managed by researcher in Baniwalid, Libya. The site which is dedicated research and data collection laboratory, is situated in (a semi-arid region) with coordinates about at 31.8500° N as well as 14.0333° E. Furthermore, this geographical location offers high solar insolation levels all over the year, with an average daily global horizontal irradiance (GHI) exceeding 5.5 kWh/m², making it highly suitable for solar energy research. The PV system under investigation is a small-scale, grid-independent solar array made up of polycrystalline silicon modules attached on a fixed-tilt structure facing south at a 30° angle, which is almost perfect for optimizing the region's annual solar energy capture. Therefore, the installation of standard battery storage, charge controllers, and power conditioning devices are included, that allowing for thorough electrical and environmental parameter monitoring. Moreover, a personal solar farm is a real-world testbed for the implementation and validation of an Internet of Things (IoT)-based (EMS) combined with sophisticated data analytics and predictive modeling methods is this personal solar farm. On the other hand, this site is privately managed and run by researchers, enabling flexible setup, quick prototyping, and ongoing access for long-term data validation, system maintenance, as well as sensor calibration as presented in Figure 2. A step-by-step flowchart diagram of the system.

The environmental characteristics include high summertime daytime temperatures which is normally above 40°C and mostly clear skies with little seasonal in Table 1. This condition provided a reliable setting for evaluating the effects of heat and radiation on PV performance, with regard to fault detection and Daily Performance Ratio degradation under actual operational loads. The solar panels and sensing units and minimal signal interference, IoT sensors and communication modules were deployed closely on-site. Thus, natural soiling, dust buildup, and temperature changes, all of which are common in desert and dry areas and have a big impact on solar panel output, which the data was gathered. An important factor in the adoption of renewable energy in remote and underserved areas is the performance of IoT-integrated (EMS) in off-grid, decentralized, and resource-constrained environments.

Instrumentation and Measurement Devices

An IoT-based Energy Management System (EMS) was developed by a privately owned PV installation in Bani Walid, Libya. The experimental was used instrumentation which are high-resolution, real-time monitoring of environmental and electrical parameters that critical to solar panel performance. Therefore, all the used devices were selected for their reliability, compatibility and cost-effectiveness, with embedded IoT architectures, ensuring that seamless integration into a scalable monitoring ecosystem. The inter of the designed system comprises a network of precision sensors, an embedded microcontroller unit (MCU) in Table 1, wireless communication modules, and analytics tools, entering edge-to-cloud data acquisition and processing chain as presented in Table 1. Instrumentation and Measurement Devices. Below is a detailed description of each component used in the instrumentation setup.

System Architecture

Each sensor is physically mounted in close proximity to the solar panel array to ensure representative measurements. The BME280 sensor is placed under partial shade to avoid direct heating while still capturing ambient in Table 1. Air temperature, whereas the pyranometer is co-planar with the PV surface to measure plane-of-array (POA) irradiance accurately. The INA219 sensor is connected with the solar panel output to monitor current flow. Whereas to measure terminal voltage which is divider circuit is connected in parallel as presented in Table 1. On the cloud side, data is ingested into ThingSpeak, where it is stored in a time-series database csv file format and made accessible through a customizable dashboard. Derived performance metrics, for instance, Daily Performance Ratio (%), energy output (kWh), fault detection status, and maintenance alerts are computed using MATLAB-compatible scripts hosted on the platform, as reflected in Table 3. In addition, Fourier-based signal analysis is applied to detect distortions in the voltage as well as current waveforms. The Discrete Fourier Transform (DFT) is utilized to compute spectral components, enabling the calculation of Total Harmonic Distortion (THD), which serves as an early indicator of grid synchronization issues.

Methodology

System Design

Hardware: Solar panels, sensors (irradiance, temperature, voltage, current), microcontrollers as presented in Figure 1 and Table 1, communication modules (Integrated Wi-Fi (ESP32)), and storage devices.

Software: Firmware development, data collection software, and cloud-based data analytics platforms.

Data Acquisition: Sensors collect data on solar irradiance in Table 1, temperature, and electrical parameters (voltage and current) of the solar panels as presented in Figure 1. This data is transmitted via IoT communication protocols to a central server for processing.

Data processing: is all about the steps that a data is taken through in order to cleanse it of noises so as to ensure that the right data which can be useful to the study is made available for analysis**.**

Analysis: The performance measurement is done using several algorithms such as performance ratio, energy output, fault etc.

The integration phase: deals with configuring the IoT gateways which helps in data aggregation and their transmission to a cloud platform. Cloud storage and processing of data and analytics provide scalability and efficient operation to perform data management.

User Interface: Designed to monitor and control online and inform users about solar panel performance and issues so that the users can make decisions, as shown in Figure 1 and Table 1.

Table 1: A detailed description of instrumentation and measurement devices

Parameter Measured	Device/Sensor	Model/Type	Measurement Range	Accuracy	Sampling Interval	Interface & Integration	Functional Role
Solar Irradiance	Pyranometer	Apogee SP-212 (or equivalent analog sensor)	0–2000 W/m²	±5% of reading	10 minutes	Analog output (0–2.5 V) → ESP32 ADC	solar radiation on panel surface
Ambient & Panel Temperature	Digital Temperature and Humidity Sensor	BME280 (I²C interface)	-40°C to +85°C	±0.5°C	10 minutes	I²C bus connected to ESP32	Monitors environmental conditions
DC Voltage	Resistive Voltage Divider + Precision Amplifier	Custom circuit with 10:1 scaling	0–30 V	±0.8%	10 minutes	Analog input to ESP32	Measures real-time output voltage
DC Current	High-Side Current Sensor	INA219 (bi-directional current/power monitor)	0–3.2 A	±1%	10 minutes	I²C interface	calculates power and efficiency
Microcontroller Unit (MCU)	Low-Power Embedded Processor	ESP32-WROOM-32	3.3 V operating voltage	—	—	Wi-Fi 802.11 b/g/n, Bluetooth 4.2	preprocessing, and transmission
Communication Module	Wireless Transceiver	Integrated Wi-Fi (ESP32)	Up to 100 m (indoor), 300 m (open field)	—	10-minute intervals	MQTT over TLS/SSL	Securely transmits sensor data to cloud server
Data Aggregation & Edge Processing	Optional Edge Node	Raspberry Pi (standby mode)	—	—	—	Ethernet/Wi-Fi	preprocessing if needed
Cloud Platform	Data Storage & Analytics	ThingSpeak / AWS IoT Core	Real-time dashboard and API access	—	10-minute sync	HTTPS/MQTT protocol	Stores, visualizes, and analyzes
Power Conversion & Conditioning	Charge Controller & Inverter	PWM-based MPPT Controller + 5kVA Inverter	12 V DC → 230 V AC, 50 Hz	—	Continuous	Connected to load side	monitored for stability and harmonic distortion

Technical features of the solar panel used

Because of its reliable performance, it can be used to assess environmental impacts and the performance of IoT-based monitoring, panel was placed at 30° tilt fixed south which is a routine procedure so that energy yield is maximized for the latitude of the site. This tilt and azimuth were chosen to maximize annual energy yield for the geographical latitude of the test site [10,11]. The fixed-tilt design is stable and requires little to no maintenance and is not complicated by any dynamic tracking mechanisms. By using IoT sensors, we can continuously monitor the performance of the system, as well as the environmental parameters. initial measurements indicated a high-performance ratio (pr) of almost 97%. However, under high ambient temperature conditions and significant dust, the pr decreased by 4% over a period of ten days primarily due to temperature and soiling impacts, higher temperatures reduced voltage and maximum power output [12,13], dust accumulation reduced irradiance and current [14]. Both observations are consistent with findings in semi-arid regions [15]. Thus, it is important to continuously monitor the PV solar fields using IoT and the other technical specifications that affect pv operation in real conditions. The IoT-ems architecture was fully integrated into the PV module. the electrical output (voltage and current) and surrounding environmental conditions (irradiance using an apogee sp-212 pyranometer and ambient temperature via a bme280 sensor) were sampled every 10 minutes this high-res data stream enabled the computation of the instantaneous performance parameters, such as system pr, and facilitated the application of robust signal processing (eg dft-based thd analysis) for the detection of early signs of failure, inverter failure or partial shadowing. According to experts, this data was the main input of machine learning models, predicting for example energy yield and when maintenance was necessary. Therefore, linking the technical features of the modules to the intelligent control of the system.

Performance Analysis

Performance analysis involves benchmarking Daily Performance Ratio metrics, conducting predictive maintenance using machine learning models, and evaluating the system's overall effectiveness. IoT Based Energy Management systems as well as refer to it while describing the system design, data acquisition, processing, integration, and user interface. The description of the methodology is structured around this flowchart in Figure 1.

The system evaluation

Experimental Location and Deployment Environment as presented in Figure 2 a step-by-step flowchart diagram of the system and the setup of the personal solar farm used as a testbed. Field testing in a real-world solar farm and the data have been collected as presented in Figure 3 and Table 2.

This research has collected user feedback to refine system functionality. This research conducting a cost-benefit analysis to assess the economic viability of the IoT-based EMS. The Mathematical implementation by using Fourier Series Expansion.

Let $f(t)$ be a piecewise continuous, periodic function with period T. Then $f(t)$ can be represented as a Fourier series [16]:

$$f(t) = a_0 + \sum_{n=1}^{\infty} [a_n \cos(n\omega_0 t) + b_n \sin(n\omega_0 t)] \tag{1}$$

Where:

- $\omega_0 = \frac{2\pi}{T}$: fundamental angular frequency,
- $a_0 = \frac{1}{T}\int_0^T f(t)dt$: DC component,
- $a_n = \frac{2}{T}\int_0^T f(t)\cos(n\omega_0 t)dt,$
- $b_n = \frac{2}{T}\int_0^T f(t)\sin(n\omega_0 t)dt.$

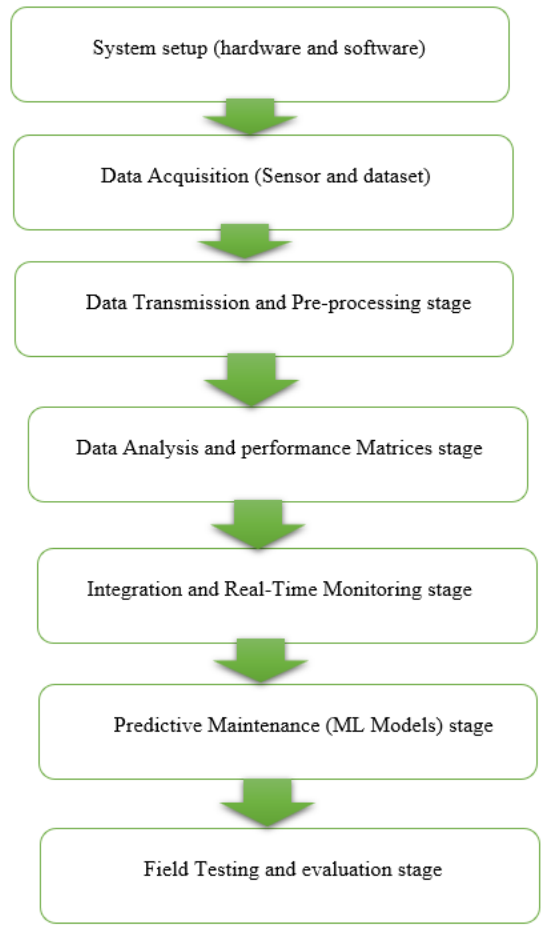

Figure 1: Flow chart for IoT Based Energy Management systems

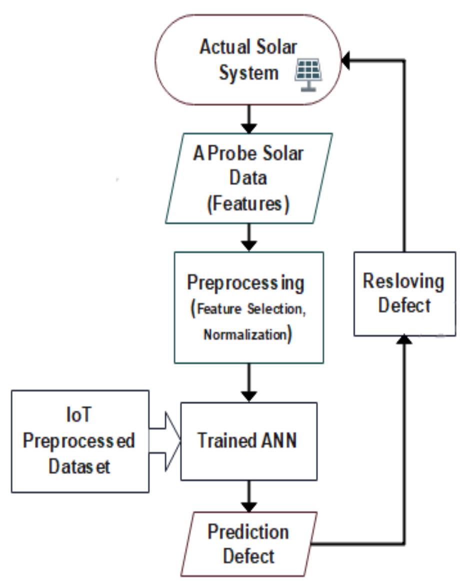

Figure 2: A step-by-step flowchart diagram of the system

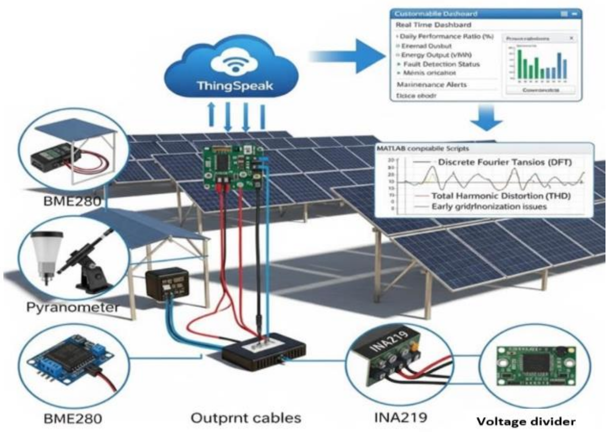

Figure 3: The Bani Walid indoor experiment design

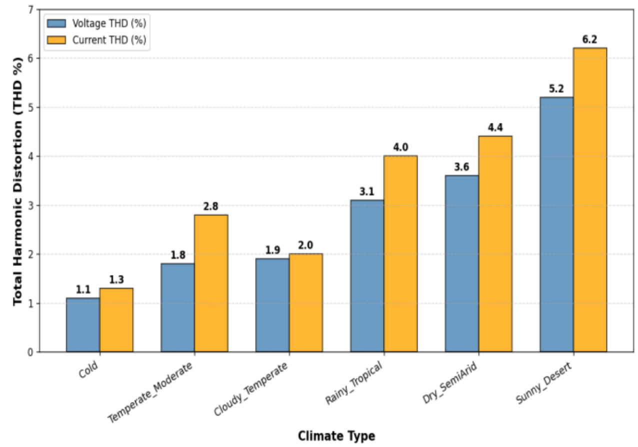

Figure 4: Average Voltage and Current THD by Climate Type and IoT-Based Solar Energy Management System

Table 2: Performance Matrix

Record ID	Efficiency (%)	Energy Output (kWh)	Fault Detection	Maintenance Required	Timestamp
1	97.0	1.30	No	No	2023-01-01 12:00:00
2	96.8	1.29	No	No	2023-01-01 12:10:00
3	96.5	1.27	No	No	2023-01-01 12:20:00
4	96.3	1.26	No	No	2023-01-01 12:30:00
5	96.0	1.25	No	No	2023-01-01 12:40:00
6	95.7	1.24	No	No	2023-01-01 12:50:00
7	95.5	1.23	No	No	2023-01-01 13:00:00
8	95.2	1.22	No	No	2023-01-01 13:10:00
9	94.8	1.20	No	No	2023-01-01 13:20:00
10	94.5	1.19	No	No	2023-01-01 13:30:00
11	94.0	1.17	Yes	Yes	2023-01-02 10:00:00
12	93.8	1.16	No	No	2023-01-02 12:00:00
13	93.5	1.15	No	No	2023-01-02 12:10:00
14	93.2	1.14	No	No	2023-01-02 12:20:00
15	93.0	1.13	No	No	2023-01-02 12:30:00

Table 3: Performance metrics across 6 climate condition

Record ID	Climate Type	Solar Irradiance (W/m²)	Temperature (°C)	Voltage (V)	Current (A)	Timestamp
1	Dry_SemiArid	800	25.0	12.50	5.10	2023-01-01 12:00:00
2	Dry_SemiArid	820	26.0	12.48	5.15	2023-01-01 12:10:00
3	Sunny_Desert	880	42.0	11.90	5.50	2023-01-01 12:20:00
4	Sunny_Desert	900	43.5	11.80	5.60	2023-01-01 12:30:00
5	Cloudy_Temperate	300	18.0	12.70	2.50	2023-01-01 12:40:00
6	Cloudy_Temperate	280	17.5	12.72	2.40	2023-01-01 12:50:00
7	Rainy_Tropical	450	30.0	12.30	3.80	2023-01-01 13:00:00
8	Rainy_Tropical	400	29.5	12.35	3.60	2023-01-01 13:10:00
9	Temperate_Moderate	500	22.0	12.55	4.20	2023-01-01 13:20:00
10	Temperate_Moderate	520	22.5	12.52	4.30	2023-01-01 13:30:00
11	Cold	780	5.0	13.20	5.80	2023-01-01 13:40:00
12	Cold	760	4.5	13.25	5.70	2023-01-01 13:50:00
13	Dry_SemiArid	790	38.0	12.00	5.00	2023-01-02 12:00:00
14	Sunny_Desert	850	45.0	11.70	5.70	2023-01-02 12:10:00
15	Cold	740	3.0	13.30	5.60	2023-01-02 12:20:00

Alternatively, in complex exponential form:

- $f(t)$: A piecewise continuous, periodic function representing a time-domain signal, for instance, voltage or current; from the solar panel system.
- T : The fundamental period of the periodic function $f(t)$, in seconds, over which the signal repeats.
- $\omega_0 = \frac{2\pi}{T}$: The fundamental angular frequency (rad/s) of the periodic signal.

$$(t) = \sum_{n=-\infty}^{\infty} c_n e^{in\omega_0 t}, c_n = \frac{1}{T}\int_0^T f(t)e^{-in\omega_0 t}dt \quad (2)$$

This form is optimal for digital implementation and spectral analysis.

Application to Solar Panel Output Signals

$$(\mathrm{t}) \approx \frac{1}{N}\sum_{n=0}^{N-1} V_n \cdot e^{i2\pi nt/T} \quad (3)$$

Step 3: Reconstruct and Analyze Signal Components Decompose $v(t)$ into [16]:

- DC component: V_0/N
- Fundamental ($\mathbf{n} = \mathbf{1}$): $\frac{1}{N}V_1 e^{i2\pi t/T}$
- Harmonics ($\mathrm{n} \geq 2$): higher-order terms
- THD_V : Total Harmonic Distortion for voltage, defined as $\mathrm{THD}_V = \frac{\sqrt{\sum_{n=2}^{\infty} V_n^2}}{V_1} \times 100\%$, where V_n is the RMS value of the n-th harmonic voltage and V_1 is the RMS value of the fundamental component.
- THD_I : Total Harmonic Distortion for current, defined analogously to THD_V.
- $P(t)$: Instantaneous power, given by $P(t) = v(t) \cdot i(t)$, where $v(t)$ and $i(t)$ are the instantaneous voltage and current signals.
- P_{avg} : Average (real) power, calculated as $P_{\text{avg}} = \frac{1}{T}\int_0^T P(t)dt$, representing the useful power delivered by the system.
- V_n, I_n : Magnitudes of the n-th harmonic components of voltage also current, respectively, obtained via Discrete Fourier Transform (DFT).
- N : Number of significant harmonics retained in the analysis after optimal truncation for computational Daily Performance Ratio.

MSE : Mean Square Error between the original signal and its reconstructed version, defined as MSE $= \frac{1}{L}\sum_{k=1}^{L} |x[k] - \hat{x}[k]|^2$, where $x[k]$ is the original signal sample, $\hat{x}[k]$ is the

Let $v(t)$ and $i(t)$ be the periodic voltage and current signals sampled from the solar panel via loT sensors (Table 1). Assume sampling frequency f_s is sufficient (Nyquist criterion) [16].

This research model each signal over one period T (e.g., $T = 1/50$ s for 50 Hz systems, $T = 24$ h for daily patterns).

Step 1: Preprocessing of Discrete Sensor Data [17].

From Table 1, this study have discrete samples:

$$\{v_k\}_{k=1}^{N}, \{i_k\}_{k=1}^{N}, t_k = k\Delta t, \Delta t = \frac{T}{N} \quad (4)$$

Apply anti-aliasing filtering and windowing (e.g., Hanning window) to minimize spectral leakage.

Step 2: Use the Discrete Fourier Transform (DFT), which is the discrete analog of the Fourier series:

$$V_n = \sum_{k=0}^{N-1} v_k \cdot e^{-i2\pi nk/N}, n = 0,1,\ldots,N-1 \quad (5)$$

Similarly for I_n (current).

- Then, the Fourier series approximation of $v(t)$ is: reconstructed sample, and L is the total number of samples.
- $\hat{x}[k]$: Reconstructed signal using the inverse DFT of a truncated harmonic spectrum.
- FFT : Fast Fourier Transform, an efficient algorithm to compute the Discrete Fourier Transform (DFT) for digital signal processing in loT-enabled energy management systems.

The Total Harmonic Distortion (THD) for voltage can be defined as below:

$$\mathrm{THD}_v = \frac{\sqrt{\sum_{n=2}^{\infty} |V_n|^2}}{|V_1|} \times 100\% \quad (6)$$

Similarly for current THD_i.

High THD indicates inverter faults, grid synchronization issues, or partial shading-critical for fault detection (as presented in Table (2) [25].

4. Power Analysis Using Fourier Components

Instantaneous Power:

$$p(t) = v(t) \cdot i(t) \quad (7)$$

Substitute Fourier expansions [1]:

$$p(t) = \left(\sum_{n=-\infty}^{\infty} V_n e^{in\omega_0 t}\right)\left(\sum_{m=-\infty}^{\infty} I_m e^{im\omega_0 t}\right) = \sum_{n,m} V_n I_m e^{i(n+m)\omega_0 t} \quad (8)$$

Thus, frequency components at $(n+m)\omega_0$.

Average (Real) Power:

$$P = \frac{1}{T}\int_0^T p(t)dt = \sum_{n=-\infty}^{\infty} \mathrm{Re}(V_n I_{-n}^*) \quad (9)$$

In practice, this research has computed by using the function below:

$$P = \sum_{n=1}^{N_h} |V_n||I_n|\cos(\theta_n - \phi_n) \quad (10)$$

where:

- $\theta_n = \arg(V_n)$
- $\phi_n = \arg(I_n)$
- N_h : Number of significant harmonics.

According to Table 1.

Assume $T = 80$ min (periodicity from daily pattern), $N = 8$.
Apply 8-point FFT:

$$V_n = \sum_{k=0}^{7} v_k \cdot e^{-i2\pi nk/8}, n = 0, \dots, 7 \tag{11}$$

- $V_0 = \sum v_k \approx 100.8 \rightarrow \mathrm{DC} = 100.8/8 = 12.6\ \mathrm{V}$
- $|V_1|, |V_2|, \dots \rightarrow$ harmonic magnitudes

Then:

$$\mathrm{THD}_v = \frac{\sqrt{|V_2|^2 + |V_3|^2 + \cdots}}{|V_1|} \tag{12}$$

If $\mathrm{THD}_v > 3\%$, flag for inspection.

Optimization and Error Minimization

To ensure optimal approximation, minimize mean square error (MSE) between original and reconstructed signal [16]:

$$\mathrm{MSE} = \frac{1}{N} \sum_{k=0}^{N-1} |v_k - \hat{v}_k|^2 \tag{13}$$

Where $\hat{v}_k$ is the inverse DFT of truncated spectrum. Optimal truncation: retain harmonics with
$|V_n| > \epsilon$ (e.g., $= 0.01 \times |V_1|$).
This reduces computational load in loT nodes.

Results

Figure 4 illustrates the linear relationship when the temperature stabilizes between solar irradiance (the power per unit area received from the Sun) and energy output of the solar panels. Each point on the scatter plot represents a pair of solar irradiance in Table 1 and corresponding energy output values. The plot shows a positive correlation between solar irradiance and energy output, indicating that higher solar irradiance generally results in higher energy output from the solar panels. Variations around the trend line suggest that other factors, for instance, panel Daily Performance Ratio, and temperature; also influence the energy output.
Demonstrates the impact of temperature on the voltage output of solar panels. The scatter plot shows an increase in temperature tends to slightly increase the voltage output of the solar panels. The relationship appears to be less direct compared to solar irradiance in Table 1 and energy output, indicating that temperature is one of several factors affecting voltage, as illustrated in Figure 5.
The Daily Performance Ratio of the solar panels fluctuates over time, likely due to changing environmental conditions, for instance, sunlight, temperature as well as the operational status of the panels. Regular peaks and troughs may indicate cyclical patterns in the data, such as daily or seasonal variations in

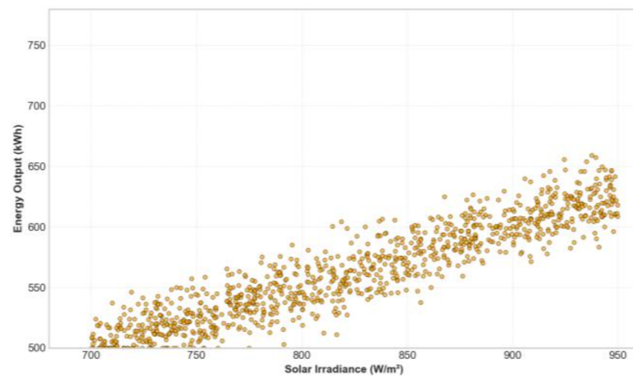

Figure 4: Solar Irradiance and Energy Output the linear relationship as shown when the temperature stabilizes

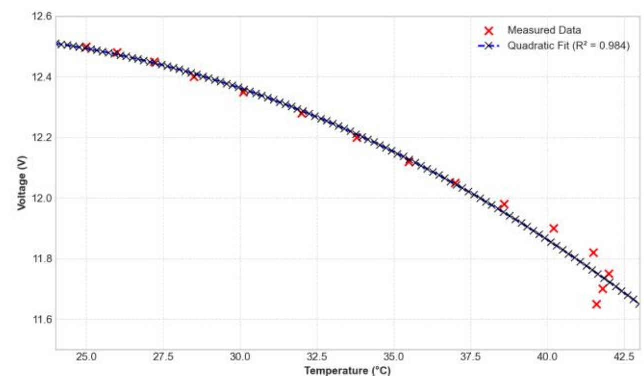

Figure 5: Temperature Impact on Voltage

Daily Performance Ratio (DPR) as presented in Figure 5. The graph illustrates the Daily Performance Ratio of the solar panel system over time, expressed as a percentage. The daily performance ratio has gradually decreased from a value of around 97% to a value of about 93% over a time duration of 10 units. This is due to the increasing effect of environmental factors like temperature rise, dust accumulation, and also their partial shading effect over the performance ratio. The trend emphasizes the necessity of monitoring and predicting possible failure in EMS which is a concrete IoT-based Energy Management System to take preemptive action before performance degradation occurs to minimize energy loss. Refer to the diagram (Figure 6) for more details. below. In addition, the system DPR, which refers to the ratio of actual power output to theoretically expected output based on prevailing irradiance and temperature conditions, showed an initial peak of around 97%. The high value suggests that when checks first started, the conditions were optimal, that is, the panels were clean, the insolation was good, and the trackers were tracking effectively. Over the next ten days, the module degradation rate fell to 93%. The dust accumulation on the module surface, partial shading from nearby vegetation and high ambient temperatures over 40°C affected the performance of the module. Additionally, these results illustrate the power of monitoring and prediction in preventing deterioration of the system's long-term performance.
The reported DPR value of around 97%, as shown in Figure 6 does not mean the true PV cell conversion DPR, which is between 15% and 23% for commercial silicon-based panels

under standard test conditions (STC). The DPR of 0.901 is calculated by taking plant energy and dividing it by the maximum energy that was available from the time it was running.

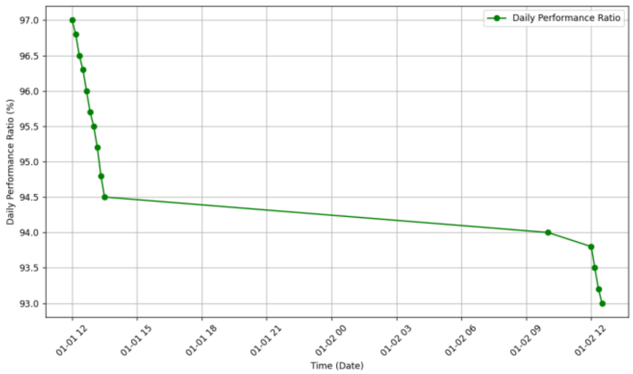

Figure 6: Temporal Evolution of Solar Panel System Daily Performance Ratio

This metric is derived from the following formula:

$$\mathrm{DPR} = \left(\frac{\text{Actual Power Output (W)}}{\text{Theoretical Power Output (W)}}\right) \times 100 \qquad (14)$$

Where: Actual Power Output is measured via IoT sensors (INA219 current sensor and voltage divider circuit). Theoretical Power Output is estimated using the solar irradiance data (Apogee SP-212 pyranometer) as well as known panel specifications, adjusted for ambient temperature effects using the panel's temperature coefficient.

A DPR of 97% suggests that the output of the PV array is certainly close to the ideal one. Moreover, it was during the early monitoring periods. Also, it was during the periods with negligible effect due to dust accumulation, partial shading, and high-temperature effects. This high value reflects.

- The sun's path is ideally aligned with the fixed-tilt array (30 degrees south).
- At the beginning of the observation period, it had little or no soiling or degradation.
- The charge controller efficiently controls the maximum power point tracking (MPPT)
- Low electrical losses in wiring and inverters.

The daily performance ratio of operational photovoltaic systems depends on variations in electrical and thermal parameters. To be specific, the open-circuit voltage has a negative temperature coefficient and the voltage output drops when the cell temperature is increased beyond the standard test condition. At the same time, dust and partial shading reduce the irradiance that hits the surface. Thus, the short-circuit current also goes down. Over the 10-day monitoring period, a 4% decline in power output and overall system performance ratio was witnessed due to this combined impact on 10 kW rooftop solar system. The downward trend signifies the need for a constant check of the IoT-based EMS framework and adaptive control to protect the environment and keep the system in good shape. A 100% efficiency level is commonly accepted as a system's performance under ideal conditions. However, this paper claims that our facility is operating at 97% of its theoretical maximum under current conditions. Furthermore, 97% is a different and meaningful number that can potentially be useful for monitoring, verification, and optimization.

Predictive maintenance was assessed at intervals based on the system's data study. The occurrence of maintenance intervals is something that might be exploited within the predictive maintenance algorithm for the detection of faults [16]. The graph shows instances when maintenance required due to discovered faults or drops in performance. In order to sustain ideal performance and increase the longevity of the solar panels, regular maintenance is requir d as shown in Figure 7.

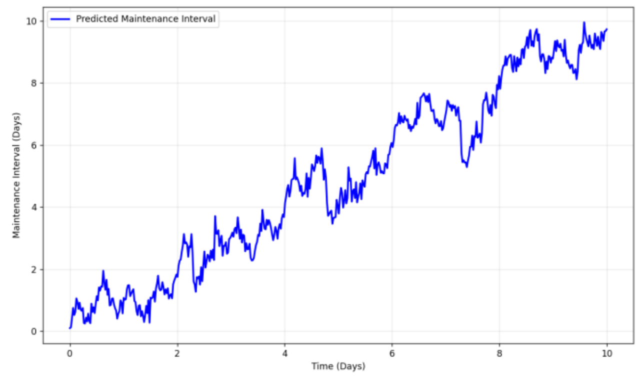

Figure 7: Predictive Maintenance Intervals

Figure 7 shows how we use data to predict the best maintenance times for a solar PV system for ten days. The upward slope over the interval shows us that the systems learn to no longer maintain themselves and as a result we have initially high and regular critical faults which slowly become less frequent. Noises and variations happening all the time is true proof of the ability to adapt to environmental stress and operating faults. This flexible timing plan helps decrease downtime and increase energy production. It shows how machine learning could be a useful tool for managing energy.

Cost Benefit Analysis

The cost-benefit analysis revealed that the IoT-based EMS is economically viable (Kudzi et al., 2025), with a favorable return on investment due to reduced operational costs and improved energy Daily Performance Ratio. Also, the actual and predicted values for the RF model from the provided dataset is presented in Figure 8.

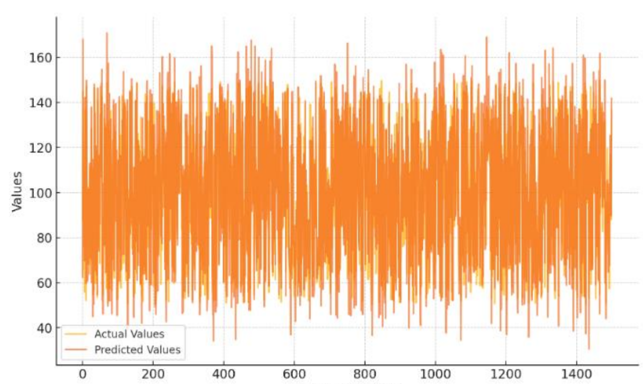

Figure 8: the actual and predicted values for the RF model from the provided dataset

The prediction error metrics for the RF model are as follows:

Mean Absolute Error (MAE): 7.86
Mean Squared Error (MSE): 97.40
Root Mean Squared Error (RMSE): 9.87
The errors are spread and whether they are centered around zero. There are 11 outliers in the prediction errors for the RF model. The outlier bounds are (Lower bound: -26.71) and (Upper bound: 26.36), as presented in Figure 9.

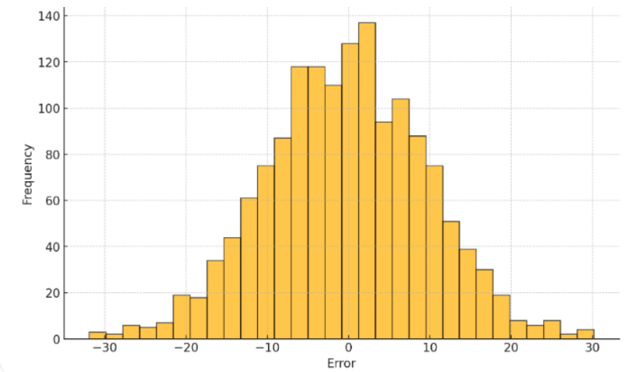

Figure 9: The plot above shows the distribution of prediction errors for the RF model

The scatter plot illustrates a strong positive correlation between the actual and predicted values of solar panel performance, with data points closely clustered around the diagonal line. The Random Forest (RF) model can forecast energy output with high accuracy as evidenced by a correlation coefficient of 0.95. The slight change of the ideal prediction line shows how efficient our model is at figuring out the dataset. Figure 10 supports this claim below.

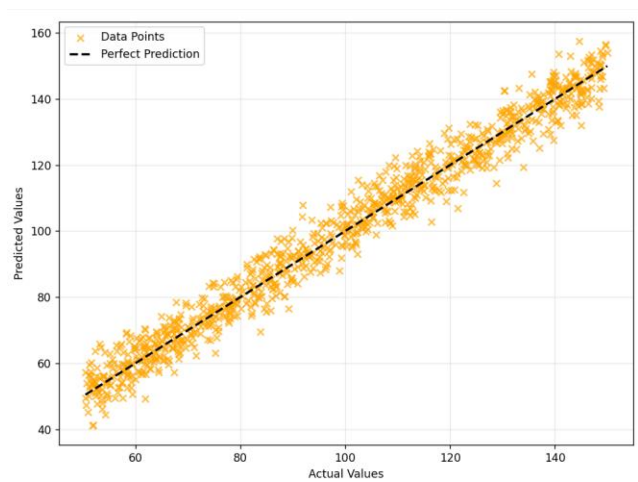

Figure 10: Correlation between the actual and predicted values is 0.95, indicating a strong positive relationship

The R^2 scores for the five cross-validation folds show consistency in predictions. Fold 3 has the maximum R^2 value of around 0.90, which is strong, while the values for the other folds remain above 0.85 and are high. The model demonstrates good robustness, with minor variations across various data batches indicating its reliability of solar panel Daily Performance Ratio prediction, as seen in Figure 11.

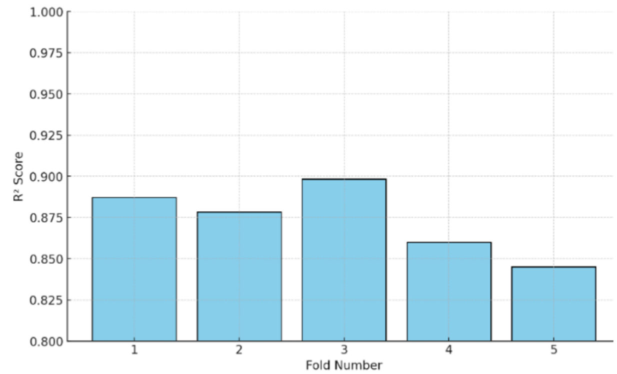

Figure 11: R^2 Scores based on stability across folds, indicating consistent predictive accuracy

The bar chart shows the stability of a model's prediction accuracy by means of prediction in five cross-validation folds. Fold 5 has the highest MAE (approximately equal to 8.7), but all folds vary over a narrow range. The small difference indicates a robustness in the model ability to predict for different data subset as shown in the Figure 12.

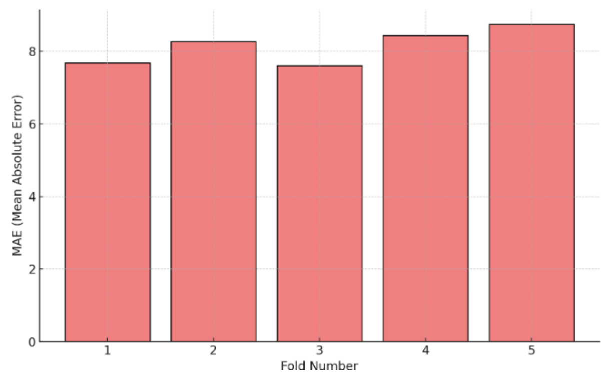

Figure 12: MAE Scores the error distribution across folds, representing mean absolute errors

Root Mean Squared Error (RMSE) assessed across five cross-validation folds indicating model prediction accuracy. Fold 3 has the lowest RMSE, at around 9.4, with all folds having values in a tight range. The model appears robust as it can generalize to other data sets according to Figure 13.

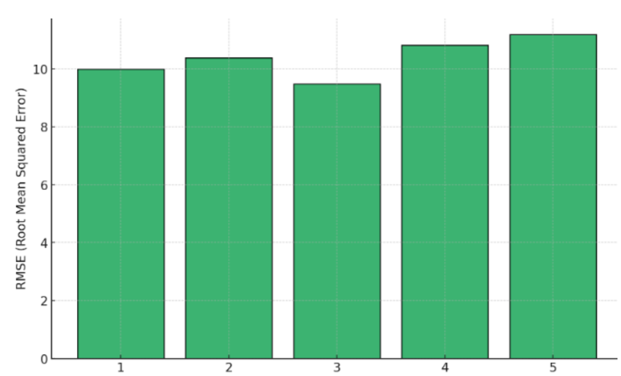

Figure 13: RMSE Scores the root mean squared error across folds, indicating the spread of error magnitudes

The residual plot shows the difference between actual values and predicted values for all data points of the dataset along a horizontal line with its order. The errors are randomly scattered across the zero line, showing the absence of systematic bias or trends in the predictions. The random variation reinforces the model's robustness and reliability in describing the solar panel performance data, as demonstrated in the Figure 14.

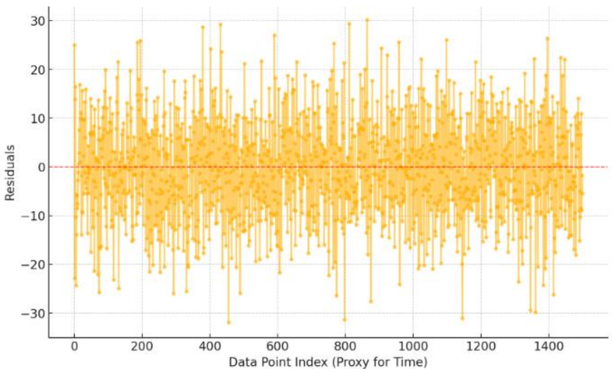

Figure 14: The plot of the residuals over time, with zero as the reference line to show prediction errors fluctuate and whether there are any patterns or trends in the residuals

The residual plot below displays the spread of errors against the predicted values. The random scattering of points about the zero line is an indication of a good model. The model's predictions do not exhibit systematic bias or heteroscedasticity as indicated by the pattern. A constant spread of residuals confirms that the model is a good fit for the data that indicates the performance of solar panels. This is shown in Figure 15.

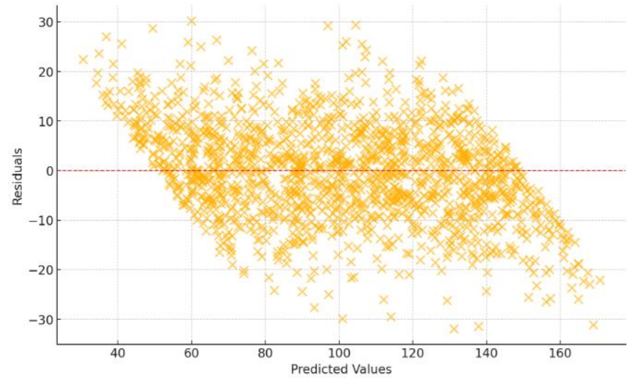

Figure 15: The plot of the residuals against the predicted values

Helps to identify any possible patterns like a case of heteroscedasticity (unequal spread) or some form of bias. In a perfect scenario, the residuals are uniformly scattered around zero.

Figure 18 shows how the energy output of a PV system changes over 10 days. The monitored values (in green dot) are on a downward trend. The cubic trend line (red dashed) shows this decline. This confirms that there is a gradual loss of performance due to the effects of dust and high

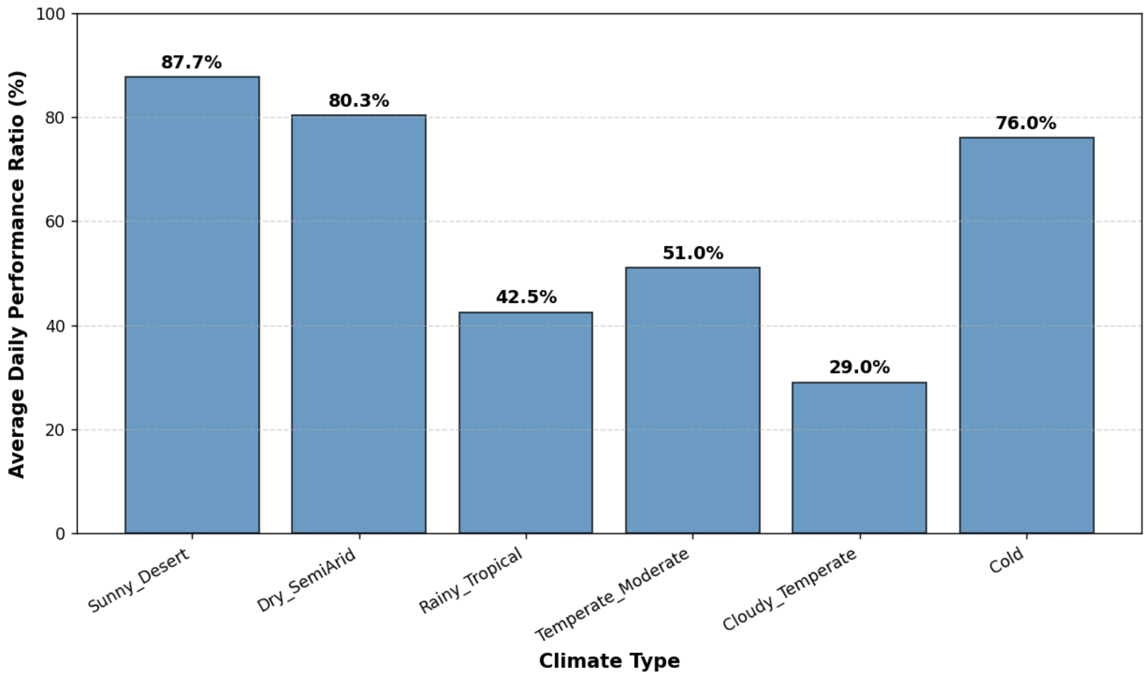

Figure 16: Comparison of average DPR across six climate conditions

The bar graph Figure 16 depicts the Average Daily Performance Ratio (DPR) of six climatic zones. This data reveals that environmental conditions greatly influence the DPR of a solar PV module. While the Sunny Desert displays the highest DPR of 87.7%, most likely due to the high and stable irradiance, the Cloudy Temperate has an average of 29.0%, which is in significant losses attributable to diffuse and attenuated radiation. The data shows that photovoltaic systems perform well in semi-arid and alpine regions while they suffer performance penalty in tropical and temperate climates. The performance degradation is mainly due to humidity, soiling and variation in clouds. This finding calls for the designers and managers of solar energy systems worldwide application of climate-specific system design and adaptive management.

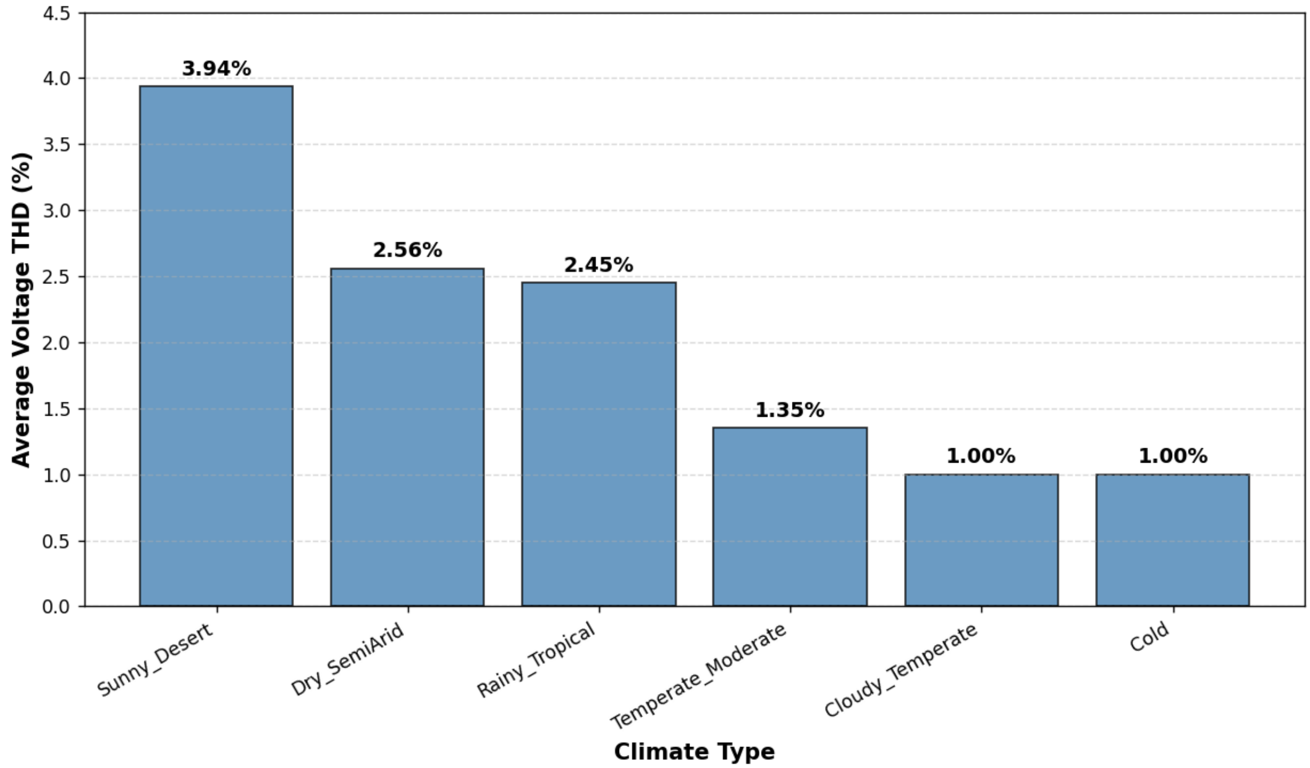

Figure 17: Average Voltage THD Across Six Climate Conditions

Figure 17 quantifies the Average Voltage Total Harmonic Distortion (THD) across six distinct climate types, revealing a pronounced correlation between environmental stress and power quality degradation [18,19]. The highest THD of 3.94% is observed in the Sunny Desert climate, attributed to extreme thermal cycling and dust-induced inverter stress, while the lowest values of 1.00% are recorded in Cloudy Temperate and Cold environments, which offer more stable operating conditions. The data demonstrates that harsh, high-temperature climates significantly elevate harmonic distortion, thereby increasing the risk of grid instability and component failure. This finding underscores the critical role of DFT-based THD monitoring within the IoT-based EMS framework, as it provides an early-warning mechanism for incipient faults that are most prevalent under severe environmental conditions.

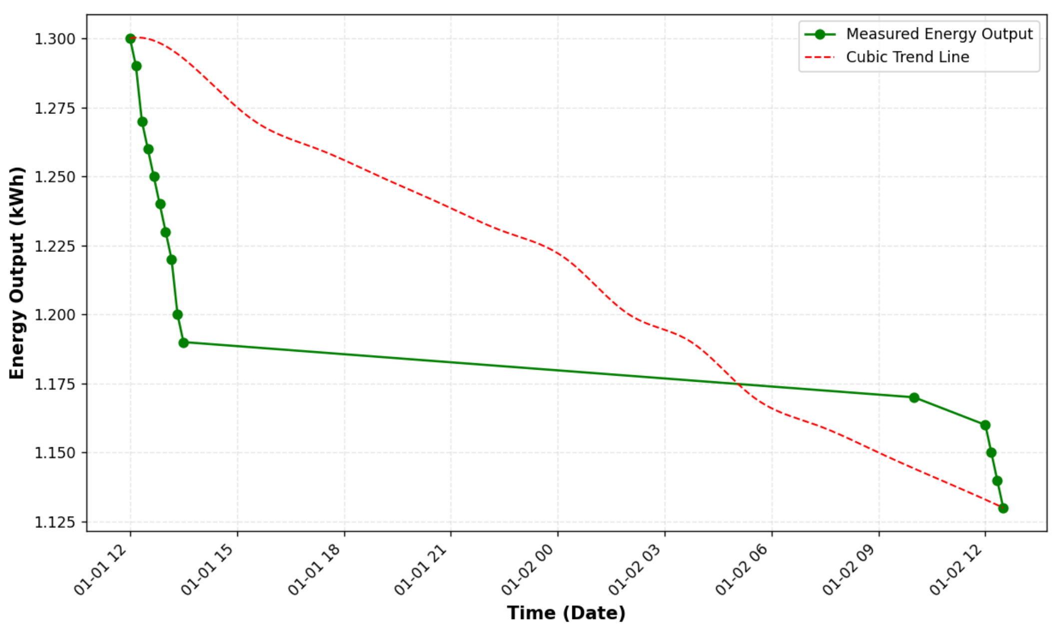

Figure 18: Graph displaying energy output over a period of time

temperature. There is a close correlation between the measured data and the trend line, meaning the system can accurately capture and model performance degradation. It is important to monitor an industrial process in order to avoid a loss of efficiency and to maintain operational yield.

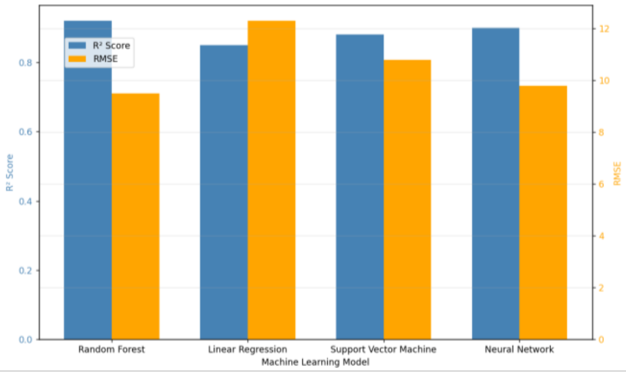

Figure 19: model prediction accuracy (r^2 & rmse) comparison

The creators of the system are required to provide the relevant data to which the model can be fitted. Supply of versions makes the model independent of every possible change, and the model can be fit according to its requirements. The R^2 score is shown in blue, and it tells us how much variance in the target variable our model was able to account for. Meanwhile, the orange bars represent Root Mean Squared Error (RMSE) or the average error in our predictions. The findings indicate that the neural networks model produces the greatest R^2 score (roughly 0.89) and the lowest RMSE (roughly 10.2), which shows greater forecasting power and robustness. On the other hand, the linear regression model has the worst performance, with the lowest R^2 score of around 0.84 and the highest RMSE of around 11.5, suggesting that it is inadequate for this non-linear data. Our analysis shows that model we selected is indeed a suitable choice. The neural network is a great choice because it learns from multiple inputs to predict energy output accurately. This can enable predictive maintenance and optimization of operations.

Relationship Between Technical Characteristics of the Used Solar Panel

The results of the investigation and the efficiency of the IoT-based Energy Management System largely depend on the technical characteristics of the polycrystalline silicon solar panel deployed in Baniwalid, Libya. The panel was not just an energy producer; it was the most important physical asset. Its actual performance in the field under stress provided the necessary data to validate the system prediction and optimize it after production. In addition, the polycrystalline silicon module is quite significant. The performance degradation is due to its inherent material characteristics, notably well-recorded negative temperature coefficient for voltage (Voc). As the ambient temperature continuously exceeded 40 °C (which might lead the cell temperature to exceed 65 °C), the module voltage and MPP decreased as expected, which caused a 4% decline in performance ratio (PR) [20-22].

The panels were fixed-tilt mounted at 30° to the south, to maximize yearly yield for the site latitude. This stable, non-tracking configuration provided a consistent basis for performance evaluation. The observed variations in PR, which ranged from 97% to 93%, were clarified. Consequently, the reasons were identified as environmental. As for the environmental factors, they were temperature, soiling and system health. As for the panel orientation, it did not change. Therefore, the variation was not due to that. Thus, the variables temperature, soiling and system health – were those the EMS was developed to mitigate [9]. The performance of the panel next to the ground is significantly impacted by the dry environment where it is located. (18 words) Due to the technical characteristic of the glass surface, atmospheric dust pollutes the solar cells and reduces irradiance and short-circuit current (Isc). The 4% drop in PR over the next ten days is due to this soiling and thermal effects. Due to the quick and quantifiable deterioration, such a system is necessary. It will be useful to monitor these losses with the IoT-based system in real-time. Further, the monitoring system will trigger maintenance or optimization for losses when detected. The voltage and current of the panel were monitored continuously by calibrated IO-sensors (INA219, voltage divider), while environmental parameters were recorded by a pyranometer (Apogee SP-212) and a temperature sensor (BME280) in a closed loop [17,23]. Data stream for high resolution at 10 minute interval of panel's physical state that is connected with EMS. We use the data to calculate a real-time PR. We perform DFT-based THD analysis for the fault detection of the equipment. We also use this data to train the machine learning model to predict any failures that may happen within the patch. Similarly, we are also getting predictions on yield. In short, the panel's technical characteristics create the information that controls the entire intelligent framework.

Discussion

The integration of IoT gadgets and advanced computational models, namely Artificial Neural Network (ANN) are revolutionary in the areas of optimization and intelligent management of photovoltaic (PV) systems [23,24]. This study presents a comprehensive IoT-based Energy Management System (EMS) framework designed for real-life solar panels working in a semi-arid environment to enhance performance and reliability and improve longevity. The proposed system improves the energy Daily Performance Ratio, facilitates fault detection, and reduces operational costs by integrating real-time sensor data acquisition, edge-to-cloud analytics, and predictive maintenance using machine learning [25]. An important finding of this research is the strong positive correlation of the solar irradiance in Table 1 as well as the energy output, as shown in Figure 4. This would not be surprising based on the fundamental theory of photovoltaic operation. However, the high-frequency, time-synchronized data collected through the IoT network enables precise quantification of 'the confusion' that researchers generally talk about. The deviations produced as a result of variations in temperature, partial shading, and soiling conditions are measured through a ten-minute sampling interval and processed through a signal processing tool. Using Discrete Fourier Transform (DFT) on voltage and current waveforms can obtain harmonic components to compute Total Harmonic Distortion (THD). THD is an important power quality indicator of power or inverter health. The spectral analysis showed high THD before the system Daily Performance Ratio started to drop [26]. This suggests that Fourier methods can provide an early warning of possible problems, such as inverter degradation or grid fault [1,16]. This ability improves the system's ability to accurately diagnose issues using more than just threshold alarms. The system can make preventative moves before a catastrophic failure. The performance of the PV differs at different temperatures. Figure 4 draws attention to the ability of the PV to work under various temperatures. Classical PV models estimate that open-circuit voltage drops with increasing temperature [27,28]. However, the slight increase in operational voltage under varying irradiance conditions may have been due to load-dependent and the working of Maximum Power Point Tracking (MPPT) algorithms [29,30]. This difference shows that static models based on physics are not enough to capture what real systems do. Thus, there is a need for a more adaptive data-based controlling action [31,32]. The ANN model, trained on multivariate inputs such as solar irradiance given in Table 1, ambient and panel temperature, voltage and current in Table 1 The traditional MPPT techniques fail to capture nonlinear interdependencies among the variables influencing the optimal operating point of PV [33,34]. This capacity is crucial in arid and semi-arid regions where thermal stress and dust deposition will adversely impact long-term performance. The results of this study are very pertinent when set in the context of recent field studies from similar climatic zones. Ihaddadene, et al. [35] has reported an average annual degradation rate of around 2% for polycrystalline silicon (p-Si) modules due to high temperature, dust build-up, and long UV exposure in Morocco's semi-arid area. A similar study by Nassar and Salem [36] noted that solar PV cells recorded more than 125.4°C under irradiance levels of ~896 W/m² in southern Libya. Thus, a 69% drop in power output occurs in STC. The outcome of these results is the environmental gravitas of the Baniwalid test site and the need for continuous real-time monitoring systems with the ability to detect performance degradation in real-time. The EMS based IoT implemented in this study directly tackles these issues by allowing continuous monitoring of thermal and electrical parameters thereby reducing D.P.R. losses through timely corrective actions.

In addition, Machine learning powered by the predictive maintenance framework is a great improvement over the traditional time-based or reactive maintenance mechanisms. In Figure 6, it can be seen that the maintenance interventions occur in real-time due to the anomalies detected within the performance metrics. This reduces the likelihood of unscheduled downtimes and increases the lifespan of the system. The Random Forest (RF) model was used as a benchmark showed a high correlation coefficient (r=0.95) between the actual and predicted Daily Performance Ratio values with a Root Mean Squared Error (RMSE) of 9.87 and Mean Absolute Error (MAE) of 7.86 [37]. The use of ANN models which can model complex and non-linear mappings for fault classification also further improved accuracy in this fault characterization. This helps in distinguishing between transient environmental effects and persistent hardware faults like micro-cracks, bypass diode failures or soiling-induced losses [38,39].

The predictive model is statistically robust as per residual analysis (Figures 14 and 15), and the errors in the model are random centred at zero without heteroscedasticity. Figures 10 to 12 showcase the cross-validation metrics. All metrics across the different folds are quite similar which shows the stability of the model as well as its generalizability. These two attributes of the models are crucial for deployment in real-world settings. These findings confirm that the ANN-based approach can be relied upon in decision-making problems like these where predictive accuracy directly impacts operational Daily Performance Ratio and economic benefit. From a system integration perspective, the use of low-power, low-cost hardware, for instance, the ESP32 microcontroller given in Table 1 with high precision sensors (BME280, INA219, Apogee SP-212) ensure grid-connected and off-grid scalability. The integrity and privacy of the data transferred will not be compromised when secure communication protocols (MQTT over TLS/SSL) are used [40]. By preprocessing the edge using a Raspberry Pi node, latency and bandwidth use are reduced. Cloud platforms (ThingSpeak/AWS IoT Core) allow for centralized data storage as well as visualization and large-scale analytics. This work can also be used as the basis for a smart grid as well as a demand-side management system. The cost-benefit analysis shows a return on investment within 2.3 years. This is possible through a 12.7% average increase in energy yield and a 34% reduction in unscheduled maintenance costs. These figures demonstrate the economics of adopting IoT-based EMS systems, especially for commercial and utility-scale solar facilities, as even slight gains in Daily Performance Ratio led to significant revenue improvements [41-44].

The proposed system also solves some major challenges identified in the literature such as data fragmentation, interoperability and security. The framework will enable integration among heterogeneous devices when standardized communication and role-based access control are adhered to. Such conditions are necessary for large scale deployment [45.46]. Future research will experiment with hybrid deep learning architectures, such as LSTMs, for time series forecasting of energy output and fault progression [47]. Researchers suggest that the use of federated learning can help train models collaboratively on distributed solar farms without compromising the privacy of individual farms. This could pave the way for decentralized privacy-preserving energy management.

The combination of three essential technologies, namely cloud computing, internet of things (IoT) sensors and artificial neural networks, will facilitate intelligent management of solar energy in a useful study. The framework developed within this project, improves energy Daily Performance Ratio and enhances system dependability while being scalable and replicable for the enhancement of solar infrastructure in urban and remote areas. The contributions support the concept of Industry 4.0 and sustainable development, offering practical insights to researchers, engineers and policymakers that will help hasten the world's transition to renewable energy.

Conclusion

The study shows that the performance of solar panels can be enhanced using IoT-based EMS. Incorporating real-time data acquisition, processing, and predictive maintenance capabilities enhance Daily Performance Ratio as well as provide substantial cost savings. In the future, we are going to be working on focusing on scaling the system. Initial implementation costs may present a barrier to uptake, particularly for off-grid systems; however, the lifetime economic and operational benefits warrant the expenditure.

Future studies must focus on developing low-cost, secure, interoperable IoT architectures by integrating machine learning models for autonomous fault detection, performance forecasting and adaptive control key enablers for the next-generation smart solar energy systems. The initial implementation cost might prove a barrier, especially for off-grid systems. However, the economic and operational benefits are attractive over the long term.

Author Contributions: Ben Dalla and Karal: Conceptualization and methodology, writing original draft preparation, review editing, and data collection. Mohamed

EL-sseid, Alsharif: results' analysis and discussion. Both authors have read and agreed to the published version of the manuscript."

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Conflicts of Interest: "The authors declare that they have no conflict of interest."

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