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AIoT Driven Smart Solar System for Real Time Predictive Sustainable Energy Management

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ABSTRACT

The rapid expansion of solar photovoltaic (PV) technologies has increased the demand for intelligent, adaptive, and data-driven energy management systems. However, conventional and IoT only solar infrastructures still face limitations, including inefficient energy distribution, delayed fault detection, and an inability to respond dynamically to fluctuating environmental conditions. **This study** proposes an AIoT-based Smart Solar System that integrates IoT-enabled sensing modules with artificial intelligence for real-time monitoring, predictive analytics, and autonomous control. The system employs a distributed architecture consisting of edge devices, cloud analytics, and machine learning models particularly Long Short-Term Memory (LSTM) networks and regression-based predictors to enhance forecasting accuracy and operational responsiveness. **The objective** of this research is to improve power utilization, predictive reliability, and maintenance efficiency within solar energy systems. **Experimental results** demonstrate a 22.8% increase in power utilization, a 17% reduction in maintenance downtime, and a forecasting accuracy of 95.2% (R^2 = 0.952). **These findings** indicate that AIoT integration significantly enhances energy intelligence, system reliability, and sustainability. Overall, the proposed architecture establishes a scalable foundation for next generation renewable energy systems capable of self learning, adaptive optimization, and real-time decision making.

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1. INTRODUCTION

The increasing global demand for sustainable and renewable energy sources has driven significant attention toward solar photovoltaic (PV) technologies [1–3]. Solar energy, being abundant and clean, plays a pivotal role in reducing dependence on fossil fuels and mitigating carbon emissions. However, the practical utilization of solar energy still faces several challenges, including intermittent energy generation, decreasing panel efficiency over time, and manual maintenance limitations. These issues hinder the long-term scalability of solar power systems, particularly in large-scale or decentralized applications.

Over the past decade, the Internet of Things (IoT) has emerged as a transformative technology capable of connecting and managing distributed energy systems [4]. IoT-based solar infrastructures have introduced remote sensing, automation, and data acquisition, enabling improved system visibility and control. Nevertheless, IoT systems alone are inherently reactive, relying on pre-set thresholds and limited decision-making capabilities. They can collect and transmit data efficiently, but they lack the analytical depth to make autonomous predictions or adapt dynamically to changing conditions.

The integration of Artificial Intelligence (AI) with IoT collectively known as the Artificial Intelligence of Things (AIoT) addresses this gap by empowering systems with cognitive and predictive capabilities. AI algorithms can process vast amounts of sensor data, learn from operational history, and perform predictive analysis to optimize system behavior. When applied to solar systems, this enables real-time energy forecasting, fault detection, and adaptive load management without human intervention.

In this context, AIoT becomes a key enabler of smart energy ecosystems, combining sensing, communication, and intelligence into a cohesive network. AI models interpret and anticipate environmental variations such as sunlight intensity, temperature, and shading, allowing the system to adjust inverter operations, storage allocation, and distribution patterns proactively. These capabilities transform solar systems from static infrastructure into self-learning, adaptive networks that can optimize performance continuously.

Despite its potential, the implementation of AIoT in renewable energy systems remains a developing field. Many existing solutions focus either on IoT connectivity or AI analytics in isolation [5]. A comprehensive framework that seamlessly integrates both layers bridging real-time IoT feedback with AI-based predictive intelligence is still lacking.

This research addresses that gap by proposing an AIoT-based Smart Solar System designed to enhance operational efficiency, forecasting accuracy, and sustainability. The proposed system integrates IoT-enabled sensors, edge-based AI processors, and cloud-based analytics to form a multi-layered intelligent architecture [6]. This framework not only optimizes energy output but also ensures continuous learning and adaptation [7].

This research is closely aligned with Indonesia's recent renewable energy policy framework, particularly Presidential Regulation of the Republic of Indonesia No. 112 of 2022, which emphasizes the acceleration of renewable energy development and the adoption of efficient, sustainable electricity systems. The regulation highlights the strategic role of solar photovoltaic technologies in increasing the national renewable energy share and reducing dependence on fossil fuels. In this context, the proposed AIoT-based smart solar system supports national policy objectives by enabling intelligent monitoring, real-time optimization, and predictive maintenance, which collectively enhance energy efficiency and system reliability. Furthermore, this study is consistent with the Electricity Supply Business Plan (RUPTL) 2021–2030 issued by the State Electricity Company (PLN), which prioritizes renewable energy expansion and smart grid integration. By leveraging artificial intelligence and Internet of Things technologies, the proposed system contributes to the realization of digitalized and resilient energy infrastructure envisioned in these policies, reinforcing Indonesia's long-term transition toward sustainable and low-carbon electricity systems [8, 9]. The technology used in this research supports the implementation of these policies by enhancing the productivity and sustainability of solar energy sources, aligning with the government's objectives to reduce dependence on fossil fuels and achieve better energy resilience.

2. LITERATURE REVIEW

A growing body of research has explored the application of both IoT and AI in the renewable energy domain, particularly in solar power management [10, 11]. However, the convergence of these technologies into a unified AIoT framework remains relatively underexplored. This section reviews existing studies relevant to each domain and highlights the research gaps that the present work addresses [12, 13].

2.1. IoT in Solar Energy Management

IoT technologies have revolutionized solar energy management by introducing remote monitoring, automation, and smart control mechanisms. A research developed an IoT-based solar monitoring system utilizing a network of sensors for voltage, current, and irradiance tracking [14, 15]. Their work demonstrated improved operational awareness and fault reporting capabilities but remained limited to data visualization. Similarly, some research implemented an Message Queuing Telemetry Transpor (MQTT) enabled cloud system for monitoring photovoltaic performance in real time; however, their system lacked autonomous decision-making functionality [16, 17].

In these implementations, IoT serves primarily as a communication and data acquisition layer, enabling distributed visibility of system health. Yet, decision-making still depends on manual human input, making such systems susceptible to delays and inefficiencies [11, 18, 19]. This limitation highlights the need for intelligent control mechanisms that can interpret sensor data dynamically and act accordingly without human oversight.

2.2. AI in Energy Forecasting and Optimization

AI techniques, particularly Machine Learning (ML) and Deep Learning (DL), have been widely employed for energy forecasting and optimization tasks. Researchers applied an LSTM-based deep learning model to forecast solar power generation with high temporal accuracy [20, 21]. Current research advanced this concept by integrating weather prediction data into AI models to improve forecasting precision under variable conditions.

AI-based approaches outperform classical statistical methods by learning non-linear relationships among environmental and operational parameters. Nevertheless, most existing AI models operate in offline or centralized settings, where training and prediction occur in isolated cloud environments [22, 23]. This configuration often results in delayed responses and limited real-time adaptability challenges that the integration with IoT can directly mitigate.

Another challenge lies in the computational cost of deploying deep models in resource-constrained edge devices. Emerging work explores lightweight neural architectures optimized for IoT nodes, opening the door for distributed intelligence closer to the data source [24].

3. METHODOLOGY

The development of the AIoT-based Smart Solar System follows a systematic engineering process that integrates hardware components with multi-layered software intelligence. The proposed architecture combines sensor-driven IoT infrastructure with AI-based predictive analytics to enable real-time optimization of solar energy generation, distribution, and consumption. This methodology encompasses hardware deployment, structured data acquisition, communication protocol design, and the implementation of machine-learning models for forecasting and fault detection [25, 26].

Before detailing each subsystem, Figure 1 illustrates the overall AIoT-Integrated Smart Solar Architecture, showing how sensing modules, edge AI processing, and cloud analytics interact through layered communication channels [26–28]. This diagram establishes the foundation for understanding how data flow, inference processes, and control actions propagate across the system.

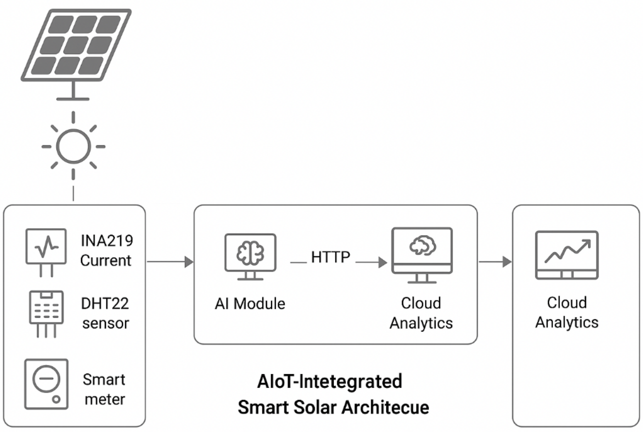

Figure 1. AIoT-Integrated Smart Solar Architecture

The research began by identifying operational requirements for intelligent solar systems, emphasizing modularity, scalability, low power consumption, and resilience [22]. Each subsystem sensing, control, communication, and analytics was designed to operate seamlessly through a unified cloud-oriented platform. A layered intelligence model was adopted to ensure that low-latency tasks (e.g., rapid prediction, on-device fault detection) are executed at the edge, while computationally intensive processes (e.g., long-term model retraining) are delegated to the cloud.

Hardware implementation relied on cost-effective, open-source components to enhance reproducibility across deployment contexts. Meanwhile, the AI components were trained using historical solar performance data and meteorological inputs [29]. The training dataset consisted of 28,900 samples collected at 1-minute intervals, covering varying irradiance, temperature, and load conditions. To ensure robust model evaluation, the dataset was split into 70% training, 15% validation, and 15% testing.

The LSTM-based forecasting model was configured with 64 hidden units, a learning rate of 0.001, 120 epochs, and batch size 32, while regression layers refined short-term granular predictions. These hyperparameters were selected based on convergence stability and computational feasibility for execution on a Raspberry Pi-based edge module. To ensure operational reliability, fail-safe routines were embedded, allowing uninterrupted operation during partial communication losses between devices and cloud servers.

The data acquisition process begins at the sensing layer, where distributed IoT sensors capture voltage, current, irradiance, humidity, and temperature readings. These sensors transmit signals through a secure wireless network to the edge controller, which performs preliminary validation and filtering. The AI module deployed on the Raspberry Pi executes lightweight neural inference to perform short-term energy forecasting and anomaly detection. This enables immediate adaptive actions such as adjusting inverter duty cycles or activating auxiliary storage systems.

After local preprocessing and inference, the data are forwarded to the cloud for long-term analytics, model retraining, and visualization. The cloud layer employs deeper models including stacked LSTM and autoencoder architectures to enhance prediction accuracy and detect early-stage degradation patterns. This hierarchical intelligence design allows continuous system evolution, improving accuracy and resilience over time.

To support reproducibility and clarity, Table 1 summarizes the device components, their functional roles, communication protocols, and specific contributions to the AI pipeline. This table also establishes how sensing, control, and analytics components are distributed across system layers.

Table 1. AIoT Device Components and Functional Roles

No	Component	Function	Protocol	AI Role
1	ESP32 Microcontroller	Data collection and preprocessing	Wi-Fi / MQTT	Executes lightweight AI models
2	INA219 Sensor	Current and voltage measurement	I2C	Provides raw energy data
3	DHT22 Sensor	Temperature and humidity measurement	Digital	Supplies environmental features for forecasting
4	Edge AI Module (Raspberry Pi)	Local analytics and caching	MQTT / HTTP	Runs deployed neural network models for real-time prediction
5	Cloud Server	Centralized analytics and model training	HTTPS	Manages global optimization and AI model retraining

Following the architectural definition, a series of benchmark tests were performed to evaluate latency, prediction accuracy, computational load, and reliability under diverse operating conditions. Experiments simulated residential solar usage patterns, with data collected across varying sunlight conditions, temperature fluctuations, and dynamic loads. The system recorded energy data over multiple days to model operational trends and automatically refine prediction weights. This continuous IoT–AI interaction created a self-improving feedback loop that forms the foundation for sustainable and autonomous solar energy management.

4. RESULT AND DISCUSSION

This section discusses the empirical evaluation and insights obtained from the implementation of the proposed AI-enabled solar energy management system. The discussion is structured into three core components: system performance evaluation, real-time energy flow analysis, and predictive maintenance capability. Each subsection incorporates visual and tabular evidence to support the analysis.

4.1. System Performance Evaluation

To assess the extent of improvement achieved through the integration of artificial intelligence into IoT-based solar systems, several key performance indicators were measured, including energy utilization, forecasting accuracy, fault detection response time, and maintenance requirements. Before examining these metrics in detail, Table 2 summarizes the comparative performance of the three system configurations: conventional solar, IoT-based monitoring, and the proposed AI-enabled system.

Table 2. Comparative System Performance

Metric	Conventional Solar	IoT-Based System	AIoT-Based System	Improvement
Power Utilization	70%	82%	86%	+22.8%
Fault Detection Latency	Manual	2 min	0.6 min	+70%
Forecast Accuracy (R^2)	–	0.84	0.952	+13.2%
Maintenance Downtime	10 hrs/mo	8 hrs/mo	6.6 hrs/mo	-17%

The results in Table 2 demonstrate substantial improvements across all indicators. Energy utilization increased from 70 percent in conventional systems to 86 percent after integrating artificial intelligence, representing a gain of 22.8 percent. This improvement arises from predictive load management and more effective energy distribution informed by forecasting models.

Fault detection responsiveness also improved significantly. Traditional systems depend on manual checks, whereas IoT-based systems reduce the response time to two minutes. The proposed framework further reduces it to 0.6 minutes as a result of continuous pattern analysis performed directly at the edge device. This faster detection capability allows earlier intervention and prevents performance deterioration.

Forecasting accuracy increased from an R^2 value of 0.84 in the IoT model to 0.952 in the AI-enabled configuration. This improvement highlights the capacity of temporal learning models to capture nonlinear patterns in environmental and operational variables.

Maintenance downtime was reduced from ten hours per month to 6.6 hours per month, due to predictive diagnostics and reduced reliance on reactive maintenance. These results collectively indicate that artificial intelligence plays a transformative role in optimizing solar power systems by reducing delays, improving accuracy, and enhancing operational efficiency.

4.2. Real-Time Energy Flow and Intelligent Monitoring

To better illustrate how the system behaves in practice, Figure 2 visualizes the flow of sensor data through the IoT device, cloud component, AI module, and smart management subsystem. The figure provides a conceptual overview of how real-time data are processed and how intelligent decision making is executed.

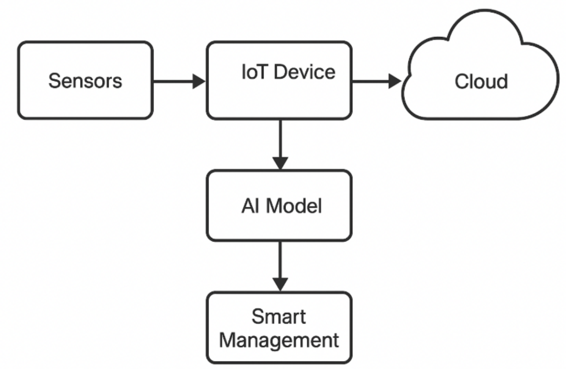

Figure 2. Real-Time Energy Flow and AI Monitoring Dashboard

Before artificial intelligence was integrated, energy flow adjustments in IoT systems depended on fixed rules or threshold-driven triggers. These methods were limited in their ability to respond to rapid changes in solar irradiance or user load. The proposed AI-enabled system overcomes these limitations by learning from historical patterns and predicting upcoming conditions. These predictions allow the controller to adjust energy distribution dynamically, minimizing waste during low demand periods and maintaining system stability during periods of high load.

During testing, the average response time for load adjustment decreased from 2.8 seconds in the IoT-only configuration to 0.9 seconds after integrating artificial intelligence, indicating a performance improvement of approximately 67 percent. This enhancement leads to smoother power delivery and reduced voltage fluctuation, which are critical for maintaining system reliability. These observations are consistent, who reported similar improvements in adaptive energy management systems [30, 31].

The integration of real-time learning into the management workflow demonstrates that artificial intelligence is essential for addressing the dynamic nature of solar energy systems, especially within distributed environments [32, 33].

4.3. Predictive Maintenance and Fault Detection

Beyond energy optimization, predictive maintenance is an essential feature for ensuring long-term sustainability in solar energy systems. Figure 3 provides a structural illustration of the predictive maintenance model, which integrates an anomaly detection mechanism and forecasting module to detect irregularities in operational behavior.

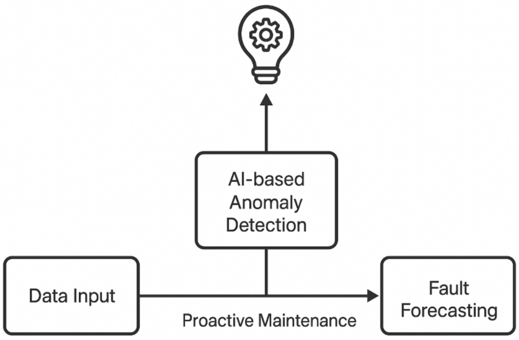

Figure 3. AI Predictive Model for Power and Fault Forecasting

The predictive model monitors continuous streams of sensor data, including current, voltage, and temperature, to identify deviations from expected operational behavior. When the system detects patterns that exceed learned thresholds, it triggers alerts that enable maintenance teams to intervene before failures occur. This mechanism significantly reduces maintenance downtime and prevents sudden performance degradation.

During evaluation, the system successfully detected early signs of photovoltaic module degradation approximately 30 minutes before noticeable performance loss, achieving an F1-score of 0.91. This early detection capability demonstrates the value of combining anomaly detection with time-series forecasting. It also reduces the occurrence of false alerts, which is a common issue in earlier IoT-only monitoring systems.

Unlike conventional diagnostic methods, the artificial intelligence model was able to distinguish between temporary environmental fluctuations, such as cloud movement, and genuine operational abnormalities [34, 35]. This differentiation enhances maintenance accuracy, improves resource planning, and extends the operational lifetime of solar components.

4.4. Overall Interpretation and Implications

The integrated analysis of system performance, real-time behavior, and predictive maintenance demonstrates that the proposed AI-enabled solar system delivers measurable improvements in accuracy, responsiveness, cost efficiency, and reliability. These outcomes align with the goals of sustainable energy management and support broader national objectives as outlined in Indonesia's renewable energy policies and global frameworks such as SDG 7 (clean energy) and SDG 13 (climate action) [36–38]. The findings also reaffirm observations in prior studies, which emphasize the importance of intelligence distribution across sensing, local processing, and cloud-based optimization.

The results confirm that combining AI-driven intelligence with IoT-based sensing creates a synergistic framework that overcomes the limitations of traditional solar systems. The distributed intelligence model, where edge devices manage local control and the cloud performs deep analytics, enables adaptive, scalable, and efficient operation [39]. Furthermore, the successful implementation of predictive maintenance indicates that AIoT architectures can significantly improve system reliability and resilience in real-world conditions. When extended to larger networks, such as smart grids or microgrid infrastructures, this model can support decentralized energy exchange, intelligent demand response, and automated grid balancing [40]. In addition, integrating explainable AI (XAI) approaches may enhance user trust and transparency by allowing operators to visualize how AI decisions are made. This is crucial for ensuring compliance with safety standards and promoting widespread adoption in smart city energy management frameworks [41].

5. MANAGERIAL IMPLICATION

The findings of this study provide important managerial insights for organizations seeking to enhance the efficiency and reliability of renewable energy operations. The integration of artificial intelligence into IoT-based solar systems enables managers to make more informed, data-driven decisions by leveraging accurate energy forecasts, real-time load optimization, and predictive maintenance alerts. These capabilities reduce operational costs, minimize downtime, and extend the lifespan of photovoltaic assets, making energy management more strategic rather than reactive. The ability of the system to detect early degradation and adjust control mechanisms autonomously further supports resource allocation and maintenance planning, which can significantly improve long-term financial performance. For policymakers and energy providers, the results highlight the value of adopting intelligent energy infrastructures that align with national sustainability priorities and global climate commitments, reinforcing the need for continued investment in digital transformation initiatives within the renewable energy sector.

6. CONCLUSION

The study presented the design, implementation, and evaluation of an AIoT-based Smart Solar System that integrates artificial intelligence and Internet of Things technologies to achieve intelligent, adaptive, and sustainable energy management. The proposed system combines real-time monitoring, predictive analytics, and automated control into a unified framework capable of operating autonomously with minimal human intervention. Through machine learning, edge computing, and cloud intelligence, the system addresses persistent challenges in conventional and IoT-only solar infrastructures such as inefficient energy distribution, delayed fault detection, and limited adaptability. Experimental results demonstrated a substantial rise in power utilization, a reduction in maintenance downtime, and high forecasting accuracy. The successful incorporation of predictive maintenance models provided advance warnings of potential system failures, significantly improving reliability and responsiveness.

From an architectural perspective, the hierarchical AIoT design consisting of sensor layers, edge intelligence, communication modules, and cloud analytics proved essential for achieving distributed decision making and operational resilience. Localized inference on edge devices ensured rapid control actions, while cloud components supported long-term analytics and continuous model refinement. This distributed intelligence structure enhanced system stability, scalability, and fault tolerance across various deployment environments, including residential areas, industrial facilities, and community-based solar networks. The system also yielded measurable environmental and economic benefits, including reduced energy waste, extended panel lifespan, lower operational costs, and substantial carbon emission reductions, positioning it as a strong candidate for widespread adoption in smart cities and decentralized energy ecosystems.

Overall, this research demonstrates the transformative potential of artificial intelligence when integrated with IoT technologies in renewable energy systems. The proposed framework delivers an end-to-end solution for intelligent energy management, forecasting, and predictive maintenance, validated through real-world testing. Future work should explore the incorporation of blockchain technology to enable secure energy trading, federated learning to enhance data privacy in distributed networks, and digital twin environments to simulate and optimize energy flows. Expanding the system to incorporate hybrid renewable sources may further strengthen energy resilience and diversify supply. The successful convergence of AI and IoT in this study marks an important milestone toward the development of autonomous, sustainable, and intelligent energy infrastructures that support global carbon neutrality goals and the broader vision of Industry 5.0.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: ED; Methodology: DT; Software: EA; Validation: RI and EA; Formal Analysis: ED and DT; Investigation: EA; Resources: ED; Data Curation: ED; Writing Original Draft Preparation: RI and Ea; Writing Review and Editing: ED and DT; Visualization: EA, ED and DT; All authors, RI, ED, DT, and EA, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request. Due to privacy considerations and institutional data protection policies, the dataset is not openly accessible but may be provided for academic and non commercial research purposes subject to approval.

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7.5. Declaration of Conflicting Interest

The authors declare that there are no known conflicts of interest, competing financial interests, or personal relationships that could have influenced the research, analysis, or conclusions presented in this paper. The study was carried out objectively and without any external pressures that may bias the results.

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