

## A HOLISTIC AI-DRIVEN ENERGY-EFFICIENT IOT FRAMEWORK FOR SMART AGRICULTURE USING MULTI-RESOURCE OPTIMIZATION

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### Abstract

The rapid adoption of Internet of Things (IoT) technologies has accelerated the development of smart agriculture systems. However, existing studies predominantly focus on single-resource optimization and lack integrated artificial intelligence (AI) approaches within distributed architectures, resulting in suboptimal system-wide performance. This study proposes an AI-driven energy-efficient IoT framework that integrates the Random Forest algorithm with an edge-fog-cloud computing architecture to enable holistic multi-resource optimization. A quantitative simulation-based approach was employed using soil moisture data from the NASA SMAP dataset, with a case study in Magelang, Indonesia. The system was evaluated using key performance metrics, including energy consumption, network latency, packet delivery ratio (PDR), and water usage efficiency. The results demonstrate significant improvements, including a 28.65% reduction in energy consumption, a 31.43% decrease in latency, an increase in PDR to 96.8%, and a 20.3% improvement in water usage efficiency. Statistical validation confirms that these improvements are significant ( $p < 0.05$ ). The main contribution of this study lies in the development of a holistic AI-driven IoT framework that simultaneously optimizes energy, water, computation, and communication without trade-offs. The proposed approach offers a scalable, adaptive, and efficient solution for real-world smart agriculture systems.

Keywords: Smart Agriculture; Internet of Things (IoT); Artificial Intelligence; Energy Efficiency

### Abstrak

Adopsi teknologi Internet of Things (IoT) yang cepat telah mempercepat pengembangan smart farming. Namun, studi yang ada sebagian besar berfokus pada optimasi sumber daya tunggal dan kurang mengintegrasikan pendekatan kecerdasan buatan (AI) dalam arsitektur terdistribusi, sehingga menghasilkan kinerja sistem secara keseluruhan yang suboptimal. Studi ini mengusulkan kerangka kerja IoT hemat energi berbasis AI yang mengintegrasikan algoritma Random Forest dengan arsitektur komputasi edge-fog-cloud untuk memungkinkan optimasi multi-sumber daya secara holistik. Pendekatan berbasis simulasi kuantitatif digunakan dengan menggunakan data kelembaban tanah dari dataset NASA SMAP, dengan studi kasus di Magelang, Indonesia. Sistem dievaluasi menggunakan metrik kinerja utama, termasuk konsumsi energi, latensi jaringan, rasio pengiriman paket (PDR), dan efisiensi penggunaan air. Hasilnya menunjukkan peningkatan yang signifikan, termasuk pengurangan konsumsi energi sebesar 28,65%, penurunan latensi sebesar 31,43%, peningkatan PDR menjadi 96,8%, dan peningkatan efisiensi penggunaan air sebesar 20,3%. Validasi statistik menegaskan bahwa peningkatan ini signifikan ( $p < 0,05$ ). Kontribusi utama studi ini terletak pada pengembangan kerangka kerja IoT berbasis AI holistik yang secara simultan mengoptimalkan energi, air, komputasi, dan komunikasi tanpa mengorbankan salah satu aspek. Pendekatan yang diusulkan menawarkan solusi yang terukur, adaptif, dan efisien untuk sistem pertanian cerdas di dunia nyata.

Kata kunci: Pertanian Cerdas; Internet of Things (IoT); Kecerdasan Buatan; Efisiensi Energi

### INTRODUCTION

The rapid advancement of Internet of Things (IoT) technology has significantly transformed traditional farming into a data-driven smart farming system. Through the implementation of sensor networks, IoT enables real-time monitoring

of environmental parameters such as soil moisture, temperature, air humidity, and irrigation conditions, thereby increasing agricultural productivity and resource efficiency. Moreover, the integration of IoT with big data analytics further enhances decision-making capabilities in modern agriculture (Alahmad et al., 2023; Patil et al., 2023).

This real-time data acquisition supports predictive and data-driven decision-making in smart farming systems (Briatore et al., 2025). However, the implementation of IoT in agriculture faces various challenges, especially related to device resource limitations such as energy, processing capacity, and data communication efficiency.

Global climate change, which causes weather uncertainty, drought, and flooding, is also further complicating modern agricultural systems. This situation demands intelligent agricultural systems capable of dynamically adapting to environmental changes (Tariqul Islam et al., 2025). Furthermore, the increasing demand for food due to global population growth demands the optimization of resource use, particularly water and energy. In this context, the agricultural sector is known to consume approximately 70% of global water resources, necessitating intelligent irrigation systems to reduce waste and increase efficiency (Ullah et al., 2021).

The use of IoT in agriculture has been shown to improve operational efficiency and production yields through real-time data collection and process automation (Alharbi & Aldossary, 2021). However, traditional cloud-based approaches suffer from high energy consumption, latency, and network load due to the transmission of large amounts of data to data centers (Al-Kadhimi & Al-Raweshidy, 2019; Katal et al., 2023). This necessitates more efficient architectures such as edge-fog-cloud computing, which can process data closer to the source, thereby reducing energy consumption and improving service quality.

On the other hand, various studies have developed IoT-based solutions for energy efficiency in agriculture, such as smart water management systems that can reduce energy consumption by up to 30% and improve grid stability (Ullah et al., 2021). Furthermore, the integration of renewable energy and intelligent control technologies has also been shown to optimize water resource use by over 70% (Bouali et al., 2021). At the indoor agriculture scale, the use of IoT-based control systems also faces the challenge of high energy consumption, particularly in lighting and environmental control systems, necessitating a more intelligent optimization approach (Hadj Abdelkader et al., 2023).

Previous research has proposed various approaches to improving resource efficiency in smart agriculture. Internet of Things (IoT) technology enables the collection of real-time environmental data through sensors that monitor soil moisture, temperature, air humidity, and crop

conditions, thus supporting data-driven decision-making, such as more efficient irrigation scheduling and early pest management (Abbassi & Benlahmer, 2021; Sohail et al., 2025; Thakare & Rojatkari, 2021). In addition, artificial intelligence (AI) and machine learning have been leveraged to analyze large amounts of data to optimize the use of resources such as water and fertilizer, predict crop yields, and support adaptive and dynamic agricultural management (Rahman & Prakash, 2026; Shankar et al., 2024; Verma et al., 2025). While these approaches show significant potential, their implementation still faces various challenges, such as high initial costs, infrastructure limitations, and lack of technical knowledge, necessitating more integrated and efficient solutions to support wider adoption (Briatore et al., 2025; Moussaoui et al., 2025; Nawaz & Babar, 2025).

However, several research gaps remain that need to be addressed. First, most studies still focus on optimizing a single resource in isolation without considering the interrelationships between various resources. Second, many approaches rely on centralized or semi-distributed architectures, potentially leading to latency and energy consumption issues. Third, limited research integrates artificial intelligence with edge-fog-cloud architectures for simultaneous multi-resource optimization. Therefore, a holistic framework capable of integrating these various components is needed to achieve efficient and adaptive resource management.

Based on these challenges, this study proposes a framework called "A Holistic AI-Driven Energy-Efficient IoT Framework for Smart Agriculture Using Multi-Resource Optimization," which integrates IoT technology, artificial intelligence, and distributed computing architecture to optimize the use of multiple resources simultaneously. The purpose of this study is to develop an AI-based IoT framework integrated with distributed computing, perform multi-resource optimization (energy, water, computing, and communication), and evaluate system performance using parameters such as energy consumption, network latency, packet delivery ratio, and water usage efficiency.

The main contributions of this research include: (1) proposing a holistic AI-based IoT framework for multi-resource optimization; (2) integrating edge-fog-cloud computing with AI-based decision-making mechanisms; (3) demonstrating simultaneous system performance improvement without trade-offs; and (4) utilizing

the NASA SMAP soil moisture dataset for realistic validation.

This research uses a soil moisture dataset obtained from NASA's Soil Moisture Active Passive (SMAP) database, available from the official website <https://smap.jpl.nasa.gov/data/>, with a case study in Magelang Regency. This dataset is used to support the analysis and development of AI-based optimization models for real-time agricultural resource management.

## RESEARCH METHODS

### Types of research

This study adopts a quantitative experimental approach based on simulation and system modeling to evaluate the performance of the proposed framework. The design follows a *design science research* methodology, which focuses on developing and evaluating innovative system architectures. This approach was chosen to objectively measure system performance parameters, such as energy consumption, network latency, water use efficiency, and data communication performance. Furthermore, this study adopted design science research principles in designing and testing the proposed system model.

### Time and Place of Research

The system architecture integrates IoT sensors, edge-fog-cloud computing, and AI-based optimization. Data acquisition is performed using soil moisture and environmental sensors, which are commonly used in smart agriculture applications (Kumar & Ch, 2019; Patrizi et al., 2022). The dataset used in this study is obtained from the NASA SMAP (Soil Moisture Active Passive) database, which provides reliable soil moisture measurements for agricultural analysis (Monsiváis-Huerta et al., 2022). Data processing, model development, and system simulation were conducted computationally using Python 3.10 and supporting simulation libraries. The target of this research is an IoT-based smart agriculture system that integrates environmental sensors, communication networks, and artificial intelligence for multi-resource optimization. The data used consists of secondary soil moisture measurements from the NASA SMAP dataset, focusing on a case study in Magelang Regency, Indonesia. The sampling technique applied purposive sampling, selecting data relevant to the target agricultural conditions and a specific study period, ensuring ecological representativeness of real-world conditions.

The proposed system follows a three-tier Edge-Fog-Cloud architecture. The Edge Layer consists of IoT sensors collecting real-time environmental data (soil moisture, air temperature, relative humidity, and solar radiation). Local pre-processing, including normalization and noise filtering, is performed at this layer to reduce transmission latency below 10 ms using lightweight protocols such as MQTT and CoAP (Muangprathub et al., 2019). The Fog Layer functions as an intermediate computing gateway that aggregates data from multiple edge nodes and executes local Random Forest inference for real-time irrigation scheduling, achieving latency below 50 ms over Wi-Fi or LTE networks. The Cloud Layer hosts the primary model training pipeline, historical data storage, global multi-resource optimization engine, and monitoring dashboard, with acceptable response latency below 200 ms (Shi et al., 2016).

### AI Model: Random Forest Algorithm

The core AI component of this study is the Random Forest (RF) algorithm, an ensemble learning method that constructs multiple decision trees during training and outputs the mean prediction (for regression tasks) across all trees (Breiman, 2001). RF was selected for its robustness against overfitting, ability to handle high-dimensional feature spaces, computational efficiency for embedded inference in fog nodes, and suitability for multi-output regression tasks in smart agriculture contexts (Jeong et al., 2016; Mucherino et al., 2009).

The RF model is configured with the following hyperparameters: number of estimators (`n_estimators`) set to 100–500 trees; maximum tree depth (`max_depth`) of 10–30 levels; minimum samples per split (`min_samples_split`) of 5; mean squared error (MSE) as the node-splitting criterion for regression; and bootstrap sampling enabled to ensure diversity among trees. Hyperparameter tuning is performed using 5-fold cross-validation with grid search. The model receives five input features: (1) volumetric soil moisture content (%) from the NASA SMAP dataset; (2) air temperature (°C); (3) relative humidity (%); (4) solar radiation ( $W/m^2$ ); and (5) historical irrigation volume ( $L/m^2$ ). All features are normalized to the [0, 1] range via min-max normalization prior to training. The RF model simultaneously predicts four resource-related outputs: required irrigation volume (L), estimated energy consumption (W), computational load distribution across the Edge-Fog-Cloud layers, and network communication efficiency score. This multi-output configuration

enables coordinated, system-wide optimization rather than single-resource optimization (Kaushik & Singh, 2025). The dataset is split into 70% training, 15% validation, and 15% testing subsets. Model convergence is monitored through out-of-bag (OOB) error reduction across successive tree additions.

The research procedure was carried out in six sequential stages: (1) problem identification and literature review to understand the challenges of energy and resource efficiency in smart agricultural systems; (2) design of the three-tier IoT system architecture comprising Edge, Fog, and Cloud computing layers integrated with the AI module; (3) data collection and pre-processing, including min-max normalization, data cleansing, and missing value imputation; (4) development of the Random Forest-based multi-resource optimization model for predicting irrigation needs and supporting efficient decision-making; (5) system simulation and model testing using Python; and (6) performance evaluation and comparative analysis against a conventional baseline system. Furthermore, artificial intelligence (AI) has emerged as a key enabler in smart agriculture by providing predictive analytics and optimization capabilities (Titirmare et al., 2024). AI-driven systems can analyze large volumes of sensor data to optimize irrigation, energy consumption, and crop management (Kaushik & Singh, 2025). However, existing studies predominantly focus on optimizing a single resource, such as energy or water, leading to suboptimal system-wide performance.

### Data and analysis technique

Data analysis in this study was conducted using a quantitative approach to ensure objective and measurable evaluation of system performance. The analysis process consists of three main stages: data preprocessing, model validation, and performance evaluation using mathematical metrics. In this research, the artificial intelligence model is implemented using the Random Forest (RF) algorithm, which is employed for prediction and decision-making in multi-resource optimization. System performance was evaluated using several critical metrics, including energy consumption, network latency, packet delivery ratio (PDR), and water usage efficiency, which are widely recognized as standard indicators in IoT-based smart agriculture systems indicators in IoT-based smart agriculture systems (Haseeb et al., 2020). These metrics are commonly applied in machine learning-based optimization systems to

ensure model reliability and performance (Naser & Alavi, 2023).

### Data Preprocessing

Data preprocessing was performed to improve data quality and enhance the performance of the Random Forest model. The preprocessing steps include:

1. **Data Cleaning**

Missing and inconsistent data were identified and handled using interpolation techniques to ensure data continuity.

2. **Normalization**

All input features were normalized using min-max normalization:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

This ensures that all features contribute equally during the training process.

3. **Noise Filtering**

Outliers and noisy sensor readings were removed using threshold-based filtering to improve model robustness.

4. **Feature Selection (RF-Based)**

Feature importance derived from the Random Forest model was used to identify the most relevant variables affecting system performance. This reduces dimensionality and improves computational efficiency.

### Random Forest Model Evaluation

The Random Forest model predicts system outputs such as irrigation requirements and resource allocation. The prediction is defined as:

$$y = \frac{1}{T} \sum_{t=1}^T ft(X)$$

where  $T$  is the number of decision trees and  $ft(X)$  represents the prediction of the  $t$ -th tree

### Model Validation

To ensure model reliability and generalization, k-fold cross-validation was applied:

$$CV = \frac{1}{k} \sum_{i=1}^k Error_i$$

Additionally, the dataset was divided into: 70% training data, 15% validation data, 15% testing data

This validation approach ensures that the Random Forest model performs consistently across different data subsets and avoids overfitting.

### Performance Metrics

#### 1. Energy Consumption

$$E_{total} = \sum (E_{tx} + E_{rx})$$

#### 2. Latency

$$Latency = T_{transmission} + T_{processing}$$

#### 3. Packet Delivery Ratio (PDR)

$$PDR = \frac{N_{received}}{N_{sent}} \times 100\%$$

#### 4. Water Usage Efficiency

$$WUE = \frac{Water_{used}}{Water_{supplied}} \times 100\%$$

#### 5. Mean Squared Error (MSE)

$$MSE = \frac{1}{n} \sum (y_i - \hat{y}_i)^2$$

#### 6. Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

### Data, Instruments, and Data Collection Techniques

The data used in this study include environmental data, such as soil moisture, as well as system performance data generated from simulations, including energy consumption, latency, throughput, and water usage efficiency. Soil moisture data were obtained from the NASA SMAP dataset, which has been widely used for agricultural monitoring and analysis (Colliander et al., 2021; Monsiváis-Huertero et al., 2022). Simulation-generated data include packet delivery ratio (PDR), end-to-end latency, and per-tier energy consumption logs across the Edge-Fog-Cloud topology. The simulation environment is configured with 50 IoT sensor nodes distributed across a 100 m × 100 m agricultural field, using the IEEE 802.15.4 wireless sensor network (WSN) protocol with an initial energy budget of 2 Joules per node and a total simulation duration of 1,000 seconds.

System simulation and model implementation were carried out using Python 3.10 with the following libraries and tools: scikit-learn 1.3 for Random Forest model training, hyperparameter tuning, and evaluation; NumPy 1.24 and Pandas 2.0 for data manipulation and pre-processing; Matplotlib 3.7 and Seaborn 0.12 for result visualization; and NS-3 (Network Simulator

3) for IoT network communication simulation, including PDR and latency measurement. These tools collectively provide a reproducible and transparent experimental environment consistent with established simulation-based research practices in IoT-based smart agriculture (Navarro et al., 2020).

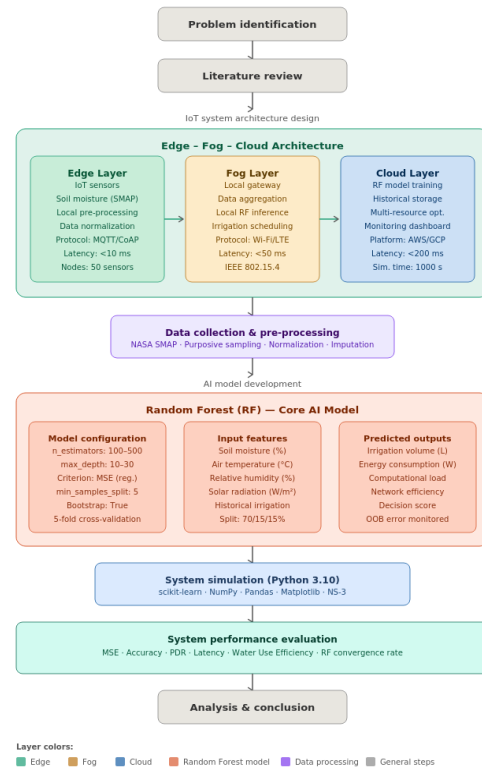


Figure 1. Flowchart research methodology

## RESULTS AND DISCUSSION

The results of this study were obtained through simulation experiments based on the NASA SMAP dataset, comparing the performance of the proposed system with a conventional IoT-based agriculture system. The evaluation focuses on key performance indicators, including energy consumption, network latency, packet delivery ratio (PDR), and water usage efficiency. The developed system utilizes multiple sensors to acquire real-time environmental data, as shown in Table 1.

Table 1. Sensors and Parameters Used in the Proposed Smart Agriculture System

Sensor Type	Measured Parameter	Unit
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Soil Moisture Sensor	Soil Moisture Level	%
Temperature Sensor	Ambient Temperature	°C
Humidity Sensor	Air Humidity	%
Water Level Sensor	Water Availability	cm

Based on Table 1, the use of multiple sensors allows the system to collect comprehensive environmental data. This data serves as the primary input for AI models to optimize resource utilization. This addresses the research need to develop systems that adapt to dynamic environmental conditions. To ensure the validity of the experiment, the simulation configuration is determined as shown in Table 2.

Table 2. Simulation Configuration and System Parameters

No.	Parameter	Value/Description
1	Simulation Area	100 m × 100 m
2	Number of Sensor Nodes	50 nodes
3	Network Type	WSN
4	Communication Protocol	IEEE 802.15.4
5	Initial Energy per Node	2 Joules
6	Simulation Time	1000 seconds
7	Data Source	NASA SMAP Dataset
8	Architecture	Edge-Fog-Cloud

The configuration in Table 3 shows that the system is designed to represent real-world conditions in agricultural IoT. The use of an edge-fog-cloud architecture aims to reduce communication overhead and improve data processing efficiency.

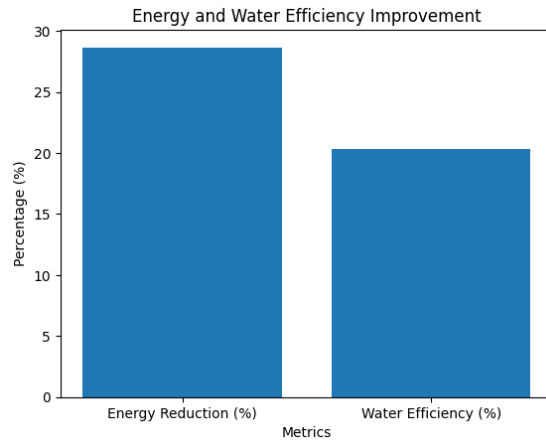


Figure 2. Energy and Water Efficiency

The graph in Figure 2 shows that the proposed system reduced energy consumption by 28.65% and increased water efficiency by 20.3%. This reduction in energy consumption occurred due to communication optimization and distributed computing, where partial processing was performed at the edge and fog layers, reducing the transmission load to the cloud. Meanwhile, the increase in water efficiency was due to the system's ability to utilize real-time soil moisture data. The AI model was able to determine irrigation needs more precisely than conventional methods based on fixed schedules. This demonstrates that the integration of sensor data and AI has a direct impact on resource efficiency.

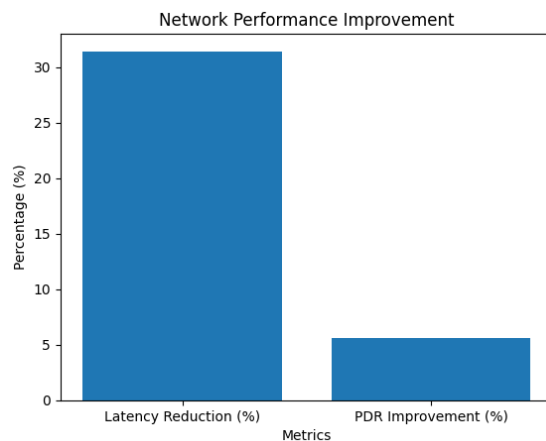


Figure 3. Network Performance

An increase in PDR indicates a more reliable system in data transmission. This is due to the optimization of communication paths and the reduction of collisions in the network. Although the increase in PDR is relatively small, it has a

significant impact on the quality of data received by the system.

To provide a clearer quantitative picture, the system comparison results are presented in Table 3.

Table 3. System Performance Comparison

Parameter	Conventional System	Proposed System	Improvement
Energy Consumption (J)	1.85	1.32	28.65% ↓
Network Latency (ms)	245	168	31.43% ↓
Packet Delivery Ratio (%)	91.2	96.8	5.6% ↑
Water Usage Efficiency (%)	68.4	88.7	20.3% ↑

Based on Table 3, it can be concluded that the proposed system achieves a comprehensive performance improvement across all evaluated metrics. Notably, the improvement in one parameter does not lead to degradation in other parameters. This indicates that the proposed multi-resource optimization approach effectively mitigates the trade-off issues commonly observed in conventional IoT systems.

In relation to the research objectives, these results demonstrate that the integration of IoT, artificial intelligence (AI), and distributed computing architecture significantly enhances overall system efficiency. From a theoretical perspective, this finding supports the concept that data-driven optimization combined with distributed computing is an effective approach to overcoming resource constraints in IoT-based systems.

Furthermore, the observed simultaneous improvement across all parameters can be attributed to the synergy among three key components: sensors (data acquisition), AI (decision making), and edge-fog-cloud computing (data processing). This integrated approach enables the system to operate not only efficiently but also adaptively and scalably, making it suitable for real-world smart agriculture applications.

## CONCLUSIONS AND SUGGESTIONS

### Conclusion

This study proposes an AI-driven energy-efficient IoT framework for smart agriculture by integrating the Random Forest algorithm with an edge-fog-cloud computing architecture to achieve multi-resource optimization. The results demonstrate significant improvements in key performance metrics, including reduced energy consumption, lower network latency, improved packet delivery ratio, and enhanced water usage efficiency. The main contribution of this study lies in the development of a **holistic multi-resource optimization framework** that simultaneously manages energy, water, computation, and communication resources without introducing trade-offs between system parameters. This finding confirms that the integration of IoT, AI, and distributed computing provides an effective, adaptive, and scalable solution for smart agriculture systems.

### Suggestion

Future work should focus on implementing the proposed framework in real-world agricultural environments to validate its performance under dynamic conditions. In addition, the integration of more advanced AI techniques, such as deep learning or reinforcement learning, may further improve system adaptability and optimization capability. The incorporation of renewable energy sources and security mechanisms is also recommended to enhance system sustainability and reliability.

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