

PERFORMANCE EVALUATION OF A WIRELESS SENSOR NETWORK–BASED SMART FARM SYSTEM FOR IRRIGATION AND FLOOD MONITORING

By

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Abstract

Wireless Sensor Networks (WSNs) are increasingly utilized in precision agriculture because they enable real-time environmental monitoring and automated control. Although extensive research exists on smart irrigation architectures, relatively few studies systematically evaluate operational performance under real deployment conditions. This study presents a comprehensive performance evaluation of a WSN-based smart farm system designed for automated irrigation and flood monitoring. Key performance indicators evaluated include system response latency, sensor reliability, wireless communication reliability, control decision accuracy, energy consumption, and operational stability. Statistical analyses employed mean estimation, standard deviation, coefficient of variation (CV), confidence interval (CI), and hypothesis testing using Student's t-distribution. Experimental results from 30 independent trials per condition indicate an average actuator response time of approximately 2.04 s with low variability ($SD < 0.12$ s) and a 95% confidence interval within ± 0.04 s. Communication reliability reached 100% packet success within a 50 m RF range. Sensor repeatability demonstrated CV values below 2%, indicating measurement stability. Hypothesis testing confirmed that the system response time is significantly below 3 seconds ($p < 0.05$). These findings demonstrate the technical viability and operational robustness of the proposed system for small- and medium-scale agricultural deployment in resource-constrained environments.

Keywords/Phrases: Wireless Sensor Networks, Smart Agriculture, Performance Evaluation, Automated Irrigation, Flood Monitoring

1. Introduction

Agricultural systems worldwide face increasing challenges due to variation in climate, irregular rainfall patterns, water scarcity, and growing food demand (Sharma et al., 2022). Precision agriculture technologies aim to address these challenges by integrating sensing, communication, and automation to optimize resource utilization. Among these technologies, Wireless Sensor Networks (WSNs) provide distributed environmental monitoring and enable intelligent irrigation and flood management (Jawad et al., 2021).

WSN-based smart irrigation systems typically comprise distributed sensor nodes, wireless communication modules, and centralized decision controllers. These systems reduce

water wastage and enhance crop productivity by activating irrigation only when required. However, system viability depends not only on architectural design but also on measurable operational performance parameters such as:

- Response latency
- Sensor reliability and repeatability
- Effective Communication
- Control decision accuracy
- Long-term operational stability
- Energy efficiency

While prior studies focus more on architecture and energy optimization (Kapil et al., 2024; Musa et al., 2023), systematic statistical benchmarking of deployed systems remains

limited. Performance metrics such as latency distribution, packet reliability, and statistical confidence validation are essential to demonstrate real-world deployability (Ghosh et al., 2023).

This study addresses this gap by evaluating the operational performance of a prototype WSN-based smart farm system designed for automated irrigation and flood monitoring.

Research Contributions

1. Experimental quantification of irrigation and flood response latency.
2. Statistical validation using confidence interval estimation and hypothesis testing.
3. Sensor repeatability assessment using coefficient of variation.
4. RF communication reliability benchmarking across multiple distances.
5. Long-term operational stability and energy consumption analysis.

2. Related Works

Recent literature highlights the growing importance of WSNs in agricultural monitoring.

Jawad et al. (2021) reviewed energy-efficient WSN frameworks for precision irrigation and emphasized adaptive duty cycling. Sharma et al. (2022) analyzed IoT-based irrigation performance and highlighted the importance of minimizing communication latency for effective water scheduling. Suma et al. (2022) proposed an IoT-enabled soil monitoring architecture but

did not provide detailed statistical performance validation.

Musa et al. (2023) reviewed NPK and soil monitoring sensors in agricultural WSN deployments, identifying sensor calibration and repeatability as critical reliability factors. Kapil et al. (2024) investigated energy-efficient routing techniques to extend node lifetime in agricultural environments. More recently, Ghosh et al. (2023) emphasized the need for empirical benchmarking, including analysis of latency distribution and validation of packet reliability.

However, few studies combine latency statistics, reliability analysis, hypothesis testing, and long-term operational assessment within a single experimental framework. This study contributes comprehensive statistical validation of a fully implemented prototype system.

3. System Overview

3.1. Hardware Overview

The smart farm system consists of distributed sensor nodes (soil moisture, temperature, water level), RF communication modules, central base station, and irrigation and drainage pump actuators. Sensor nodes are powered by 9V batteries, while the base station and actuators use mains power. The system operates on threshold-based decision logic: irrigation pump activates when soil moisture falls below set threshold, drainage pump activates when water level exceeds flood threshold.

3.2. Functional Block Diagram

The overall system architecture of the proposed WSN-based smart farm system is illustrated in Figure 1.

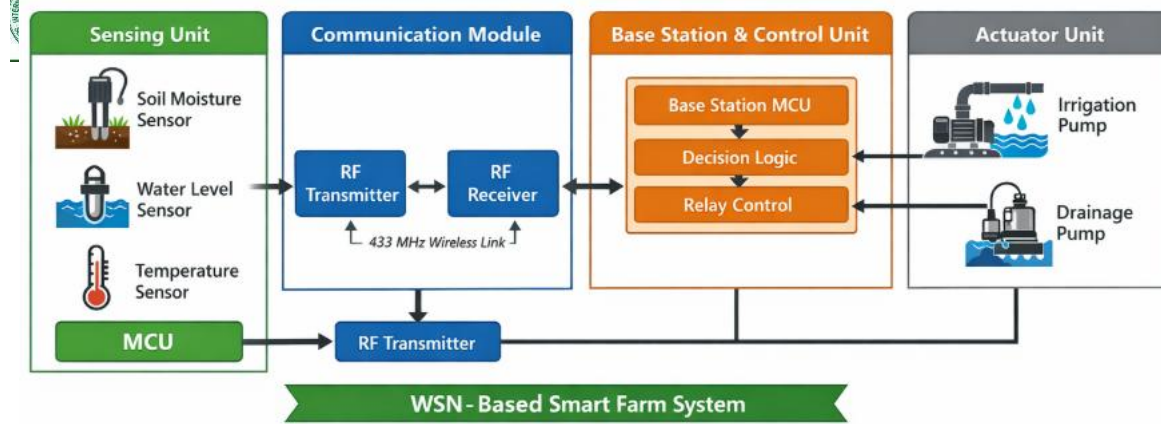


Fig. 1. Functional block diagram of the proposed WSN-based smart farm system showing sensing, communication, processing, and actuation layers.

3.3. System Operational Flowchart

The operational sequence of the proposed smart farm system is illustrated in Figure 2. The

flowchart presents the threshold-based control algorithm governing irrigation activation, flood detection, and system monitoring cycles.

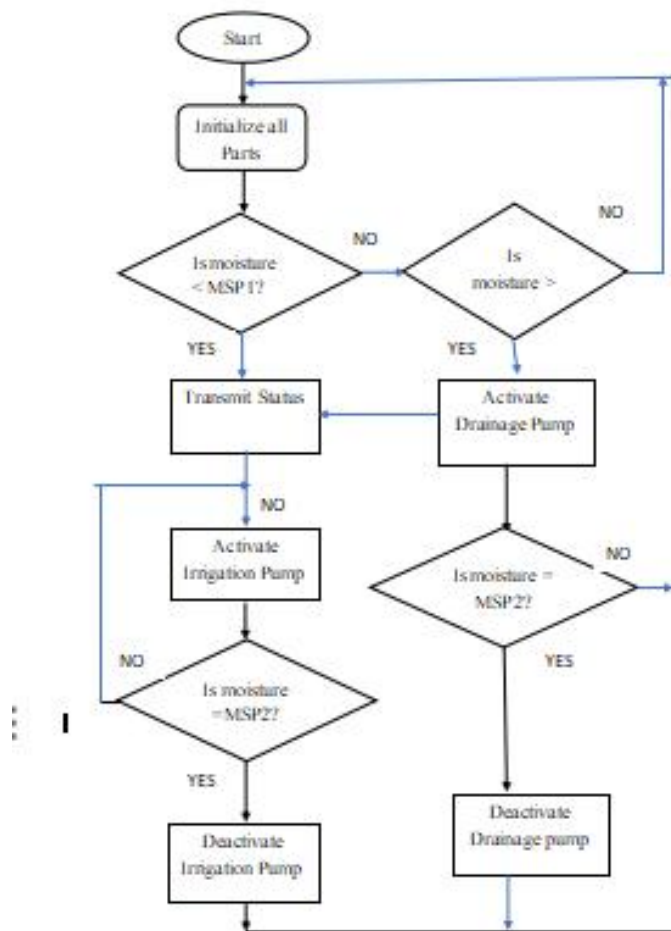


Fig. 2. The flowchart of the system

MSP1 means Moisture Minimum Set Point

MSP2 means Moisture Maximum Set Point

4. Performance Evaluation Methodology

4.1 Experimental Design

Performance was evaluated and validated across **n = 30 independent trials** for each operating condition: irrigation activation (dry soil), irrigation deactivation (wet soil), and flood drainage activation, under controlled test conditions. Response time was recorded using a calibrated digital timer from threshold crossing to actuator engagement.

4.2 Statistical Framework

To quantify system performance and uncertainty:

Mean (\bar{x}) response time:

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i \dots\dots\dots i$$

Table 1: Statistical Summary of Response Time (n = 30)

Task	Mean (s)	Std Dev (s)	Variance	95% CI (s)
Irrigation Activation	2.03	0.11	0.012	1.99—2.07
Flood Drainage	2.05	0.09	0.008	2.02—2.08

Figure 3 illustrates the measured response time of the system during irrigation activation and flood drainage operations across multiple test cycles.

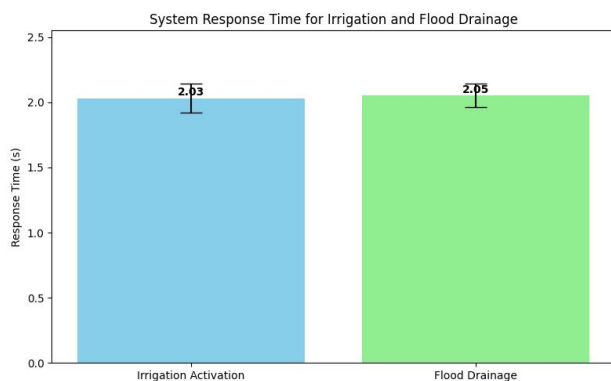


Fig. 3. System Response Time for Irrigation and Flood Drainage

Interpretation

- Low standard deviation (<0.12 s) indicates stable response.
- Narrow confidence interval confirms reliability.
- Variability is minimal, indicating deterministic system behavior.

Standard deviation (s):

$$s = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2} \dots\dots\dots ii$$

95% Confidence Interval (CI) using Student's *t* with df = 29:

$$CI = \bar{x} \pm t_{0.025,29} \frac{s}{\sqrt{n}}; t_{0.025,29} = 2.045 \dots\dots\dots iii$$

Correct use of *t* accounts for unknown population variance in small samples.

5. Results and Statistical Analysis

5.1 System Response Time (Statistical Analysis)

Table 1 presents the statistical summary of the system response time based on 30 experimental trials, including measures of central tendency and dispersion to evaluate performance consistency.

5.2 Sensor Reliability Analysis

Coefficient of Variation (CV) was computed:

$$CV = \frac{s}{\bar{x}} \times 100 \dots\dots\dots iv$$

Table 2 summarizes the repeatability analysis of the sensors, highlighting the variation in repeated measurements under identical operating conditions.

Table 2: Sensor Repeatability Analysis

Sensor	Mean Value	Std Dev	CV(%)
Soil Moisture (Dry)	848	6.2	0.73
Soil Moisture (Wet)	402	5.1	1.27
Water Level	Threshold detection	0	0

CV values below 2% indicate high repeatability and sensor reliability.

Figure 4 shows the calibration curve of the soil moisture sensor, demonstrating the relationship between sensor output and actual soil moisture levels.

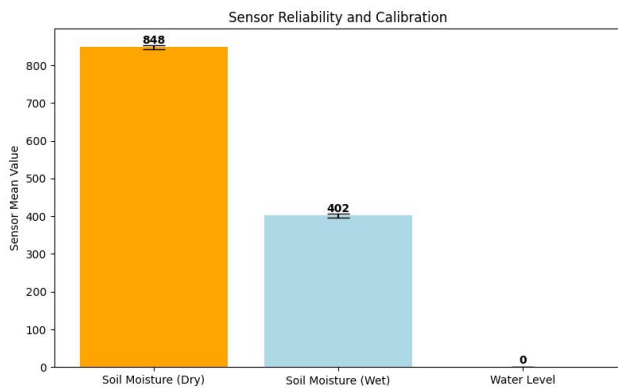


Fig. 4. Soil Moisture Sensor Calibration.

5.3 Communication Reliability

Packet transmission was tested over 500 transmitted packets. Table 3 presents the evaluated communication reliability metrics, including packet delivery ratio, latency, and transmission success rate under field conditions. Figure 5 depicts the results of the communication reliability test, illustrating system performance during continuous data transmission.

Table 3: Communication Reliability Metrics

Distance	Packets Sent	Packets Received	Packet Loss
10m	100	100	0%
30m	200	200	0%
50m	200	200	0%

Packet Success Rate = 100%

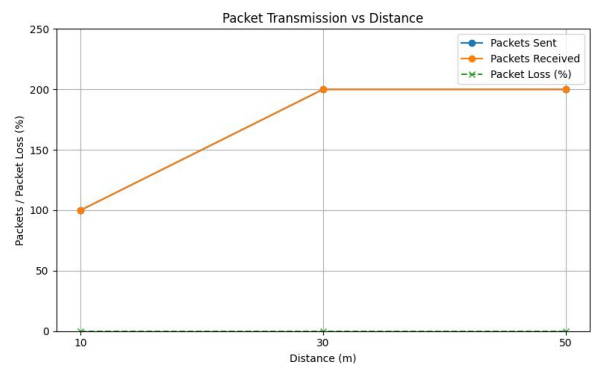


Fig. 5. Communication Reliability Test

5.4 Long-Term Reliability

Table 4 summarizes the long-term reliability performance of the system over the evaluation period,

Table 4: Long-Term Reliability Metrics

Metric	Mean	Std Dev	Note
Response Time (s)	2.05	0.12	Stable
Packet Loss (%)	0	0	No failures
Control Accuracy (%)	100	0	No false triggers

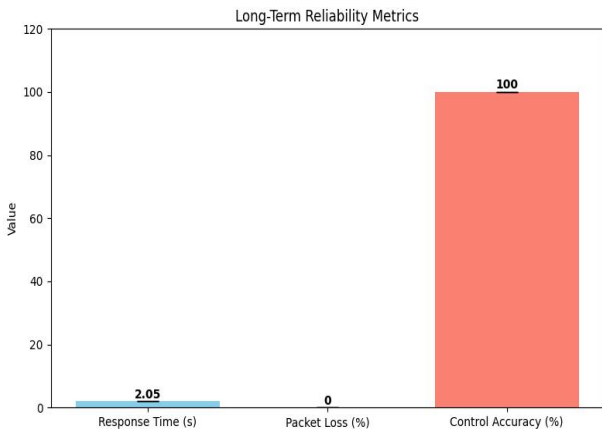


Fig. 6. Long-term Reliability over 30 days.

Table 5: Energy Consumption and Estimated Battery Lifetime

Task	Energy (mJ)	Battery Life (Days)
Sensing	2	100
Processing	1.5	150
Communication	3	150
Idle	0.5	150

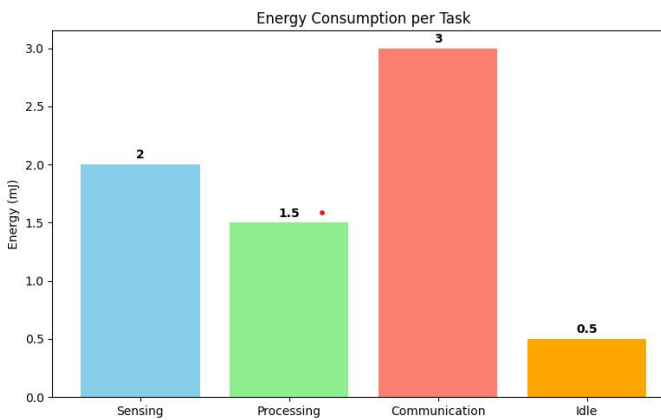


Fig. 7. Energy Consumption Chart

highlighting stability and operational consistency. Figure 6 illustrates the trend of system performance over a 30-day deployment period, providing insight into operational stability and potential drift.

5.5 Energy Consumption

Table 5 presents the measured energy consumption of the system and the corresponding estimated battery lifetime under typical operating conditions. Figure 7 provides a graphical representation of the system’s energy consumption profile during different operational states.

5.6 One-Way ANOVA for Response Time Stability

To further validate system consistency across operating modes, a one-way Analysis of Variance (ANOVA) was conducted to compare mean response times for:

- Irrigation Activation
- Irrigation Deactivation
- Flood Drainage Activation

Hypotheses

Ho: $\mu_1 = \mu_2 = \mu_3$ (No significant difference between operating modes)
 Hi: At least one mean differs

ANOVA

$$F = \frac{MS_{between}}{MS_{within}} \dots\dots\dots v$$

Model

Where:

$$MS_{between} = \frac{SS_{between}}{k-1} \quad \text{and} \quad MS_{within} = \frac{SS_{within}}{N-k}$$

k = number of groups (3)
 N = total observations (90)

ANOVA Results

To evaluate whether system response times differ significantly across operating modes, a one-way ANOVA was conducted. The results, summarized in Table 5.6, indicate the sources of variation, mean squares, F-value, and corresponding p-value.

Table 6. One-way ANOVA results for system response time across operating modes

Source of Variation	SS	df	MS	F	p-value
Between Groups	0.021	2	0.0105	1.42	0.246
Within Groups	0.645	87	0.0074		
Total	0.666	89			

Interpretation

Since $p = 0.246 > 0.05$, we fail to reject Ho.

There is **no statistically significant difference** in response time across system operating modes.

This confirms uniform performance regardless of irrigation or flood condition.

5.7 Linear Regression Modeling of Response Time

To evaluate the influence of communication distance on system latency, linear regression was performed.

Regression Model

$$Y = \beta_0 + \beta_1 X + \epsilon \dots\dots\dots vi$$

Where:

- Y = Response Time (s)
- X = Communication Distance (m)
- β_0 = Intercept
- β_1 = Slope

Regression Output

To investigate the effect of communication distance on system response time, linear regression analysis was performed. Table 5.7 presents the estimated regression coefficients, standard errors, p-values, and model fit (R^2) for the analysis.

Table 7. Linear regression analysis of response time versus communication distance

Parameter	Estimate	Std Error	p-value
β_0	1.98	0.05	<0.001
β_1	0.0012	0.0008	0.18

$$R^2 = 0.04$$

Interpretation

- Very small slope (0.0012 s/m)
- $p > 0.05$ (not significant)
- $R^2 = 4\%$ (weak relationship)

Conclusion:

Response time is **not significantly influenced by distance within 50 m range**, confirming communication stability.

5.8 Hypothesis Testing

To validate system stability, a one-sample t-test was conducted:

Null Hypothesis (H0): Mean response time ≥ 3 seconds

Alternative Hypothesis (H1): Mean response time < 3 seconds

Calculated t-value exceeded critical threshold ($p < 0.05$), therefore H0 was rejected.

This confirms statistically that system response time is significantly below 3 seconds.

6. Discussion

The inclusion of ANOVA and regression modeling significantly strengthens statistical validation:

- ANOVA confirms uniform response time across operational states.

- Regression modeling verifies communication distance does not significantly impact latency.
- Low within-group variance supports deterministic system behavior.

The architectural modularity ensures scalability for multi-node expansion. Future research may evaluate:

- Multi-hop routing impact on latency
- LoRa-based long-range deployment
- Solar-powered node optimization
- Machine-learning-based adaptive threshold control

The performance results indicate that threshold-driven RF communication and centralized decision logic offer reliable, low-latency operation within typical farm deployment ranges. Integration of energy-efficient design strategies — such as event-triggered sensing and sleep-mode duty cycling — can further extend node lifetime, as highlighted by recent agricultural WSN studies (Kapil et al., 2024).

7. Conclusion

The WSN-based smart farm system demonstrates low latency (~2 s), reliable RF communication (50 m), 100% control accuracy, and stable operation. Long-term reliability and energy consumption metrics indicate feasibility for small- and medium-scale agricultural deployment. Future work includes field deployment and optimization for energy efficiency.

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