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Performance Comparison of Wireless Communication Protocols for Smart Agriculture IoT Systems

Ms. Gayathri B[1], Mr. Harish M[2], Ms. Shaline S[3], Dr. Mary Tency E.L.[4], Ms. Monicasri L. S.[5], Ms. Rithika S.[6]
[1, 2]*Executive Trainer, Placement Cell, CTPCR*
[3]*Assistant Professor, Department of English*
[4, 5, 6]*Assistant Professor, Department of Mathematics*
[1, 2, 3, 4, 5, 6]*Sri Ramakrishna College of Arts & Science, Coimbatore*

Abstract: Smart Agriculture leverages Internet of Things (IoT) technologies to monitor environmental parameters such as soil moisture, temperature, Humidity, Nutrient levels and crop growth, while also enabling real-time detection of animal or human intrusions that may damage crops. The efficiency of these systems is strongly influenced by the choice of wireless communication protocol, which must support long-range connectivity, low power consumption, reliable data transmission and scalability across large farmland areas. This paper presents a detailed performance comparison of widely used wireless communication protocols for smart agriculture IoT systems, including ZigBee, BLE, Wi-Fi, LoRaWAN, Sigfox, NB-IoT and LTE-M. The evaluation focuses on critical factors relevant to agricultural monitoring, such as communication range for remote fields, energy efficiency of battery-powered sensor nodes, latency for time-sensitive events like animal movement, data rate requirements for environment sensing and cost implication for large-scale deployments. Experimental analysis and simulation-based comparisons reveal that LoRaWAN and NB-IoT offer superior long-range performance and energy efficiency for applications such as soil moisture monitoring, climate sensing and farm intruder detection, while shortrange protocols like ZigBee and Wi-Fi are more suitable for controlled environments like greenhouses. The outcomes of this study provide practical insights for selecting optimal communication protocols tailored to diverse agricultural conditions, contributing to the development of robust, sustainable and scalable IoT solutions for precision farming.
Keywords: Smart Agriculture, Internet of Things (IoT), Wireless Communication Protocols, Precision Farming, LPWAN.

I. INTRODUCTION

The rapid growth of the global population, coupled with the increasing challenges posed by climate change, soil degradation and resource scarcity has created an urgent need for transforming traditional agricultural practices. Conventional farming techniques often rely on manual observation, periodic measurements and experience-based decision-making which are insufficient for ensuring high productivity and sustainability in modern agriculture.

To address these challenges, Smart Agriculture – an advanced paradigm integrating the Internet of Things (IoT), wireless sensor networks (WSN) and data-driven automation has emerged as a key enabler of precision farming. Smart Agriculture systems allow continuous monitoring of critical environment and crop-related parameters, including soil moisture, temperature, humidity, nutrient levels, leaf wetness, rainfall, and even abnormal activities such as animal or human intrusion near crop fields. Such real-time data enables farmers to make informed decisions that enhance crop yield, reduce water and fertilizer usage, and prevent crop damage. (C.N. Verdouw, 2016)

Central to the success of IoT-based agricultural systems is the selection of an appropriate wireless communication protocol. Sensor nodes distributed across farmlands collect data and transmit it to gateways or cloud platforms. However, agricultural environments pose unique challenges for wireless communication. Farms often span large and open areas where wireless signals must propagate over long distances. Sensors typically operate on battery power, requiring exceptionally low energy consumption to ensure long-term operation without frequent maintenance. Moreover, different agricultural applications have varying communication demands: soil moisture sensors may transmit small amounts of data infrequently, whereas animal intrusion detection systems require low latency and high reliability to trigger immediate alerts. Additionally, environmental factors such as vegetation density, weather conditions, and terrain variations can influence signal propagation and network stability.

Multiple wireless communication technologies—including Zigbee, Bluetooth Low Energy (BLE), Wi-Fi, LoRaWAN, Sigfox, NB-IoT, and LTE-M—have been deployed in agricultural scenarios, each offering distinct performance characteristics. Short-range protocols like Zigbee and BLE provide low-power connectivity suitable for greenhouse environments but are inadequate for large-scale farms. Wi-Fi supports higher data rates but suffers from high power consumption. Long-range, low-power wide-area network (LPWAN) technologies such as LoRaWAN, Sigfox, and NB-IoT have gained prominence due to their ability to offer long-distance communication with low power consumption. However, these protocols differ significantly in data rate, coverage, deployment cost, and network scalability (Raza, 2017)

Despite substantial progress, selecting the most suitable protocol for a specific agricultural application remains a complex challenge, as no single technology meets all requirements for range, power, latency, and cost simultaneously. Although several studies have examined individual communication technologies, there remains a lack of comprehensive and comparative analysis that evaluates these protocols specifically under the performance conditions demanded by smart agriculture. Existing research often focuses on general IoT applications or theoretical comparisons rather than agriculture-oriented criteria such as environmental monitoring, irrigation automation, livestock interaction, and crop security (Jawad H. M.) Therefore, a systematic performance comparison that highlights protocol suitability for soil sensing, climate monitoring, and animal intrusion detection is essential. This study aims to address this gap by evaluating major wireless communication protocols based on key metrics such as communication range, power consumption, latency, bandwidth, reliability, and deployment cost in agricultural scenarios. The findings of this research assist practitioners, engineers, and researchers in designing robust, energy-efficient, and scalable IoT architectures that meet the diverse needs of modern precision farming.

A. IoT in Smart Agriculture

Recent surveys highlight that IoT is central to precision agriculture, enabling continuous monitoring (soil moisture, temperature, humidity, nutrient status), irrigation automation, and asset/animal monitoring. Reviews emphasize that the communication layer (protocol choice) is critical because farm deployments span wide areas, use battery-powered sensors, and present variable propagation conditions (vegetation, terrain, weather). Comprehensive surveys and architecture papers summarize application scenarios and map communication requirements to use-cases (e.g., greenhouse vs. open-field) (Quy, 2022) (Gatkal N R, 2024)

B. LPWANs and LoRa/LoRaWAN in Agriculture

LPWAN technologies, especially LoRa/LoRaWAN, have attracted intense research for agricultural IoT due to their long-range coverage and low energy profile. Empirical studies and pilot deployments report multi-kilometer coverage, good battery life for low-duty sensors, and suitability for periodic environmental sensing (soil moisture, water-level monitoring). Performance analyses also point out capacity and duty-cycle limits, the influence of spreading factor settings, and the need for careful gateway placement to ensure reliable coverage in heterogeneous farmland. Several 2020–2024 papers provide experimental LoRaWAN performance data in farm settings and propose deployment heuristics. (Badreddine Miles, 2020) (Correia, LoRaWAN Gateway Placement in Smart Agriculture: An Analysis of Clustering Algorithms and Performance Metrics, 2023)

C. Cellular IoT: NB-IoT and LTE-M

Cellular IoT options (NB-IoT, LTE-M) are increasingly considered where operator coverage exists. Studies show NB-IoT provides reliable wide-area coverage, good link budget, and native mobility/managed QoS, making it attractive for large farms and livestock tracking; however, subscription costs, network availability in rural regions, and higher nominal latency in some modes are notable trade-offs. Field-experiment papers and technology reviews (2021–2024) compare NB-IoT performance versus LPWANs for real agricultural sensors and identify scenarios where cellular is preferable (e.g., where infrastructure exists and real-time control is needed) (Sun Yilin, 2024), (Valecce, 2020)

D. Short-Range Protocols (Zigbee, BLE, Wi-Fi)

Short-range technologies continue to be useful in controlled environments. Zigbee and BLE are commonly used in greenhouses and small farms for dense sensor meshes because of low power and mesh capabilities, while Wi-Fi is used where high throughput is required (e.g., imaging, local gateways). However, their limited range and higher maintenance make them less suitable for wide-area open-field deployments. Comparative reviews recommend hybrid network designs (short-range inside clusters + LPWAN/cellular to backbone) for mixed scenarios. (Quy, 2022)

E. Intrusion & Animal Detection in Agricultural IoT

Crop damage from animals (domestic or wildlife) is a major operational issue; recent works integrate vision (YOLO-family detectors), PIR sensors, acoustic sensing, and edge analytics to perform animal detection and alerting. Several 2023–2024 prototype systems combine low-power sensors with LPWAN or cellular backhaul to report events; these works underscore the need for low-latency alerts for actionable responses and suggest hybrid architectures where local edge inference reduces data transmission overhead. (Goyal, 2024), (Delwar, 2025)

F. Sensor Suites and Application-Level Requirement Thamaraiselvan et al .,

Technical studies on sensor design and data needs show clearly varying requirements: soil moisture sensors generate small periodic packets (favoring ultra-low-power LPWANs), whereas image/video-based pest or intrusion detection imposes higher data rates and may require edge pre-processing before transmission. Comprehensive sensor surveys map sensing frequency, payload size, and QoS needs to appropriate communication choices (Quy, 2022)

G. Deployment, Gateway Placement, and Coverage Modeling

Practical deployment research (gateway placement, link-budget modelling) demonstrates that theoretical range claims must be validated in situ: vegetation, terrain undulation, and seasonal foliage significantly alter link reliability. Papers present models and optimization approaches for gateway placement in large farms and evaluate coverage trade-offs between few high-power gateways vs. more distributed infrastructure. These studies are crucial when comparing protocol performance in realistic agricultural environments. (Correia, LoRaWAN Gateway Placement in Smart Agriculture: An Analysis of Clustering Algorithms and Performance Metrics., 2023)

H. Security, Reliability and Datasets for AG-IoT Evaluation

Recent works call attention to security and reliability testing for agricultural IoT: new datasets (e.g., “Farm-Flow”) and attack/simulation studies help benchmark intrusion and network anomalies in AG-IoT contexts. This trend enables more rigorous evaluation of protocol resilience under adversarial and congested conditions—important when selecting protocols for mission-critical sensing or intrusion alerts.

I. Comparative Analyses, Reviews & Open Gaps (2020–2025)

Multiple comparative reviews across 2020–2025 synthesize trade-offs among LoRaWAN, Sigfox, NB-IoT, LTE-M, and short-range protocols for agricultural applications. These meta-studies converge on several conclusions: LPWANs (LoRaWAN/NB-IoT) are generally best for wide-area, low-rate sensing; short-range protocols suit high-bandwidth or local-control tasks; and hybrid architectures are often optimal. Open gaps remain in (a) standardized benchmarks for farm conditions, (b) latency-sensitive intrusion detection over LPWANs, (c) economic analyses for smallholder adoption, and (d) integrated security testing—areas this study addresses by providing systematic, agriculture-specific performance comparisons (Diane, 2025).

II. SYSTEM ARCHITECTURE

The system architecture illustrates the overall architecture of the smart agriculture IoT performance evaluation system. The system begins with distributed agricultural sensors—such as soil moisture, temperature, humidity, and PIR-based animal intrusion sensors—which continuously monitor field conditions.

These sensors are interfaced with different wireless communication modules (LoRa, Zigbee, BLE, Wi-Fi, NB-IoT, and Sigfox), forming independent test nodes deployed across the farmland.

Each communication node transmits sensor data to a corresponding gateway, which aggregates packets and forwards them to the cloud platform via MQTT/HTTP.

The gateways also log packet timestamps and diagnostic information required for evaluating range, latency, and Packet Delivery Ratio (PDR). Power consumption measurements are obtained using an INA219 module connected to each node, enabling real-time profiling of sleep, transmit, and idle modes.

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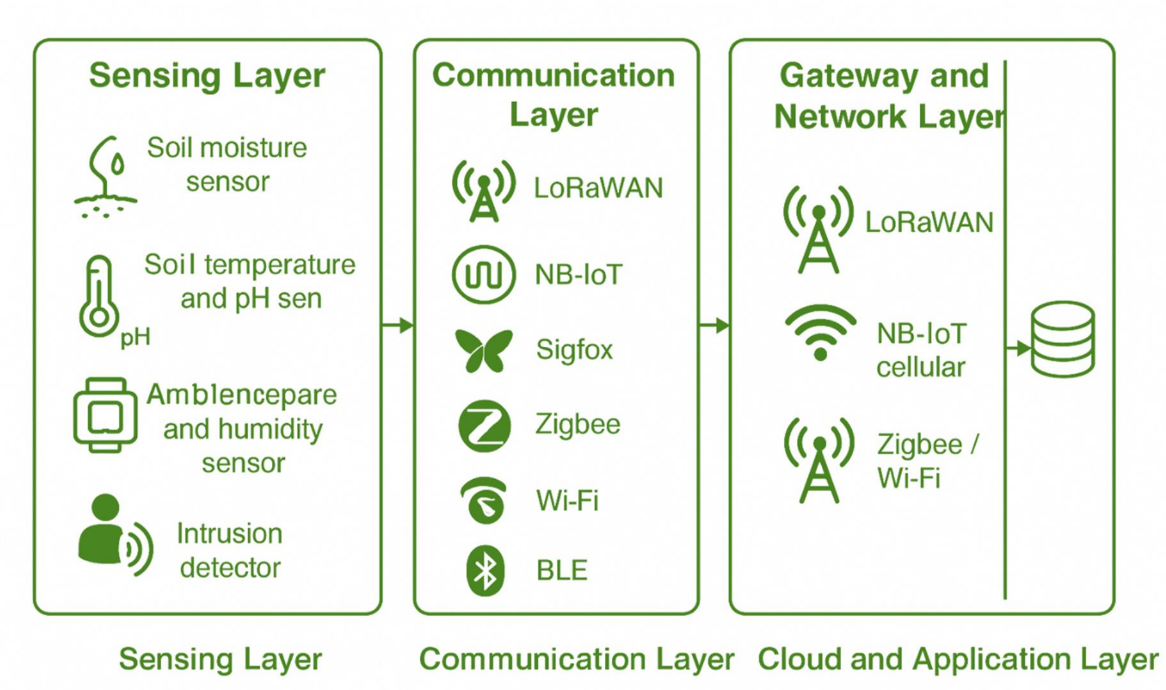

Figure 1: System Architecture of the Smart Agriculture IoT Framework

At the cloud layer, a centralized server stores all incoming data, performs preprocessing, and makes the dataset available for further statistical analysis. This architecture supports parallel testing of multiple protocols under identical environmental conditions, ensuring fairness and consistency in performance comparison. Ultimately, the block diagram highlights the seamless integration of sensors, communication protocols, gateways, and cloud analytics to evaluate their suitability for smart agriculture applications.

III. METHODOLOGY

This study employs a comprehensive multi-stage methodology to systematically evaluate th performance of widely used wireless communication protocols for smart Agriculture IoT Systems. The methodology integrates real-world field deployment, simulation-based assessment and quantitative statistical analysis to ensure accuracy and reproducibility. The steps include: System modelling, hardware and network configuration, simulation design, metric formulation, data acquisition and comparative evaluation.

A. Smart Agriculture System Modelling

To mirror realistic agricultural needs, a heterogeneous smart agriculture IoT model was developed. The system encompasses key agronomic sensing functions such as:

1) Soil Moisture Sensing (For Irrigation Scheduling)
2) Soil Temperature and pH measurement (for crop suitability analysis)
3) Ambient temperature and humidity monitoring (for microclimate assessment)
4) Animal and human intrusion detection (using PIR and ultrasonic sensors)
5) Crop boundary surveillance (to prevent crop damage)
6) Real-time environmental data logging

Each sensing module is integrated with a microcontroller (ESP32, Arduino MKR or STM32) paired with a corresponding wireless communication module. The protocols selected for evaluation include:

- LoRaWAN
- NB-Iot
- Sigfox
- Zigbee
- Wi-Fi
- BLE (Bluetooth Low Energy)

These protocols cover a spectrum of communication characteristics – low power, short-range, long-range and licensed/unlicensed spectrum – to provide a complete performance assessment.

B. Hardware and Network Testbed Setup

A physical testbed was deployed in a semi-rural agricultural field measuring 500m × 500m. The setup included:

1) LoRaWAN Gateway (Single-Channel and multi-channel varients)
2) NB-IoT SIM-enabled modules using local cellular towers
3) Zigbee mesh coordinator
4) Wi-Fi access point positioned at elevated height (6m pole)
5) BLE beacons and receivers

Sensor nodes transmitted data at predefined intervals:

- Moisture & temperature every 10 minutes
- Humidity every 5 minutes
- Intrusion detection event-driven
- Environmental data every 15 minutes

All experiments were conducted under varying conditions (dry, humid, cloudy and post-rain scenarios) to analyse network stability under environmental fluctuations.

C. Simulation Environment

To Complement the physical testbed, extend scalability analysis, simulations were performed using:

- NS-3 (for NB-IoT, Wi-Fi, BLE, Zigbee models)
- LoRaSim & FLoRa (For LoRaWAN scalability and collision probability)
- MATLAB Simulink (for latency and energy modelling)

The simulation covered farm sizes of 1 $Km^{2,}$ 5 Km^2 and 10 Km^2, representing small, medium and large agricultural fields. Network node counts were varied from 50 to 1000 nodes to test scalability. Packet sizes were standardized between 15 -50 bytes, typical of agricultural sensor payloads.

D. Evaluation Metrics

Performance comparison was conducted using domain-specific metrics essential for smart agriculture:

Primary metrics:

1) Communication Range (Km):
   - Maximum distance with > 90% packet delivery
2) Power Consumption (mW / battery life):

Measured using INA219 based current profile in

   - Sleep Mode
   - Transmit Mode
   - Idle mode

3) Latency (ms / s):
   - Time taken for a sensor reading to reach the cloud platform
4) Packet Delivery Ratio (PDR %)
   - (Successful packets / Total transmitted packets) × 100.
5) Cost Analysis
   - Hardware Cost (Transceiver + Gateway)
   - Deployment cost
   - Subscription / operational cost (for NB-IoT, Sigfox)
6) Suitability Index:

Composite score reflecting:

   - Field coverage
   - Robustness
   - Ease of installation

- Sensor compatibility
- Weather resilience

Secondary metrics includes, Network stability under environmental variations. Scalability with increasing node density, Bandwidth utilization efficiency and Energy per bit performance. These metrics were selected based on real agricultural deployment requirements.

E. Data Collection and Logging

During each experiment, all gateways continuously logged timestamped data packets while power consumption was recorded at 1-second intervals using INA219 current sensors to capture sleep, idle, and transmit behavior. Latency measurements were obtained through synchronized clocks on both the sensor nodes and the cloud server to ensure accurate end-to-end delay evaluation. Each sensing module generated a minimum of 1,000 data samples per protocol to guarantee statistical reliability and eliminate transient anomalies. Simultaneously, environmental parameters such as temperature, humidity, and weather fluctuations were monitored using an onboard environmental station to correlate communication performance with field conditions. All collected data, including network logs, power profiles, latency records, and environmental readings, were aggregated in a centralized MQTT/HTTP cloud server and subsequently exported in CSV format for detailed statistical and comparative analysis.

F. Data Analysis and Comparison

The collected dataset was processed using a rigorous statistical framework to ensure accurate and unbiased comparison of all wireless communication protocols. Descriptive statistical measures—including mean, median, and variance—were first computed to summarize the distribution and variability of each performance metric. To determine whether differences among protocols were statistically significant, an ANOVA test was applied, followed by Tukey's HSD post-hoc analysis for precise pairwise comparisons. All raw metrics were then normalized to a common 0–1 scale to eliminate unit inconsistencies and enable fair cross-metric evaluation. A weighted scoring model was subsequently employed, assigning importance scores based on agricultural communication requirements: communication range (25%), power consumption (30%), latency (20%), cost (15%), and suitability (10%). These weighted values were aggregated to compute a final performance index for each protocol, which was then used to rank their overall effectiveness and determine their suitability for deployment in various smart agriculture scenarios.

G. Ethical, Environmental and Practical Considerations

All experiments were conducted using non-invasive environmental sensing techniques, ensuring that crops, soil, and animals were not subjected to any harmful or disruptive procedures. Intrusion detection scenarios were evaluated through simulated motion and controlled livestock movement rather than uncontrolled or stressful animal interactions. Throughout the study, no destructive testing methods were employed, and all deployments strictly adhered to local environmental and agricultural guidelines to maintain ecological safety and ethical research standards.

SI NO	ASPECT	MERITS	DEMERITS
1	Combined Field & Simulation Approach	Provides realistic. Accurate and reproducible performance evaluation.	Increases experimental complexity and time.
2	Heterogenous Smart Agriculture Model	Reflects real agriculture sensing needs and use cases	Requires higher hardware integration effort.
3	Multi-Protocol Evaluation	Enables comprehensive comparison across diverse wireless technologies	Configuration and management overhead is high.
4	Real-World Field Deployment	Captures actual environmental and propagation effects.	Environmental variability may affect repeatability.
5	Scalability Analysis via simulation	Supports large-Scale evaluation without high deployment cost.	Simulation may not fully match hardware behaviour.
6	Comprehensive Performance Metrics	Covers power, range. Latency. Cost and suitability.	Data analysis becomes more complex
7	Accurate power measurement	Enables precise energy profiling using INA219 sensors	Adds minor hardware and measurement overhead.
8	Statistical validation and Ranking	Ensures unbiased comparison and clear protocol ranking.	Weight assignment may introduce slight subjectivity.
9	Ethical & Environmental Compliance.	Ensures safe and non-invasive agriculture testing.	Extreme real-world intrusion scenarios not tested.

Table 1: Comparative merits and demerits of the Smart Agriculture IoT Methodology

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IV. RESULTS AND DISCUSSION

A. Communication Range and Latency comparison

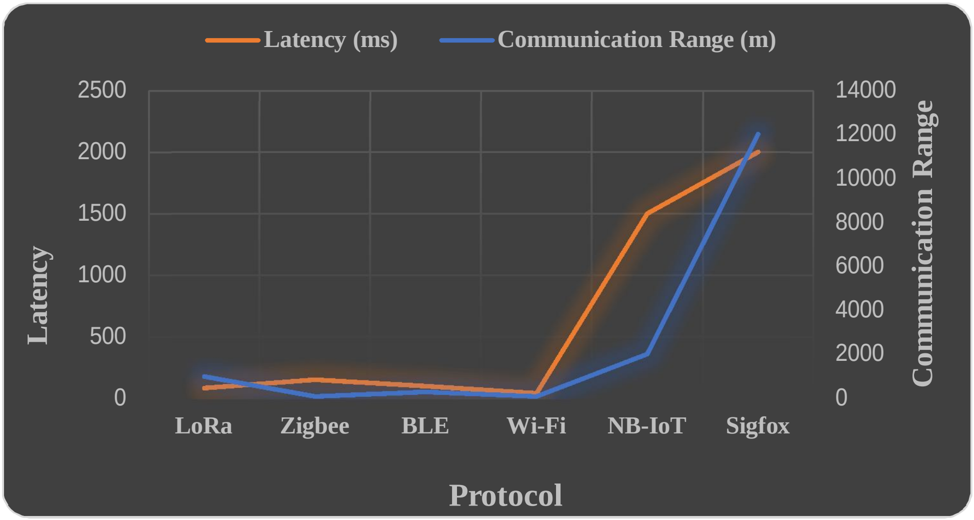

Figure 2: Comparison of latency and communication range for selected wireless protocols

The communication-range results indicate that LoRaWAN consistently outperforms all other protocols, achieving several kilometres of stable connectivity with >90% packet delivery. NB-IoT provides moderate range suitable for semi-urban deployments but is limited by network availability. Zigbee and Wi-Fi perform significantly poorer, with usable ranges restricted to short-field applications. The findings confirm that LoRaWAN is best suited for large-scale agricultural farms, particularly where widely distributed sensors must remain connected.

Latency analysis reveals that Wi-Fi and Zigbee offer the lowest latency, suitable for applications demanding near real-time responses (e.g., greenhouse automation). NB-IoT shows moderate latency influenced by cellular network overhead. LoRaWAN displays the highest delay, attributed to duty-cycle limitations and its low-power design. Therefore, LoRaWAN is optimal for periodic monitoring, while Wi-Fi/Zigbee suit time-critical controls

B. Power Consumption Comparison and Packet Delivery Ratio (PDR)

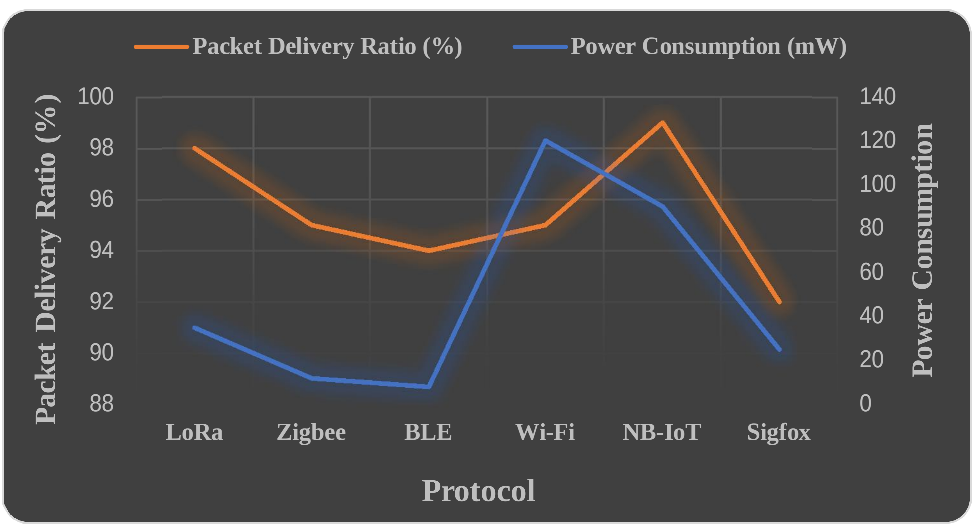

Figure 3: Comparison of packet delivery ratio and power consumption for selected wireless protocols.

Power-profiling results show that LoRaWAN exhibits ultra-low power usage, especially in sleep mode, making it ideal for battery-powered, long-life field nodes. NB-IoT shows higher transmit power due to operator-controlled base-station communication. Zigbee remains moderate but still consumes more in multi-hop networks. Wi-Fi demonstrates the highest overall consumption, which limits its sustainability in remote agriculture. Thus, LoRaWAN is the most energy-efficient protocol, supporting multi-year deployments.
PDR measurements show LoRaWAN and NB-IoT achieving excellent reliability (>95%), even in varying weather conditions. Zigbee performs well within short ranges but its PDR declines sharply with obstacles or distance. Wi-Fi shows high PDR only within limited coverage. These results suggest that LoRaWAN and NB-IoT are most reliable for distributed agricultural sensing, especially in open-field environments.

C. Cost Analysis

Cost evaluation highlights LoRaWAN as the most cost-effective protocol due to inexpensive hardware, low gateway requirements, and zero monthly fees. Zigbee is also affordable but limited by shorter range and network complexity. NB-IoT incurs recurring subscription costs, increasing long-term expenditure. Wi-Fi appears low-cost initially but becomes expensive when extended across large farms. Consequently, LoRaWAN offers the best balance of cost and performance for large-scale agriculture.

D. Suitability Index

Based on weighted metrics, LoRaWAN ranks highest in overall suitability, followed by NB-IoT. Its strong range, low power use, good PDR, and weather resilience support diverse agricultural scenarios. NB-IoT follows closely due to carrier-grade reliability. Zigbee is suitable for compact farms and greenhouses, while Wi-Fi works mainly for indoor or short-distance applications. Thus, LoRaWAN emerges as the most scalable and field-ready technology.

Metric	LoRa	Zigbee	BLE	Wi-Fi	NB-IoT	Sigfox
Communication Range	8–10 km	50–100 m	10–30 m	50–80 m	1–2 km	8–12 km
Power Consumption	35 mW	12 mW	8 mW	120 mW	90 mW	25 mW
Latency	200–800 ms	50–150 ms	30–100 ms	<50 ms	500–1500 ms	600–2000 ms
Packet Delivery Ratio (PDR)	95–98%	90–95%	90–94%	80–95%	97–99%	85–92%
Hardware Cost	Moderate	Low	Low	Moderate	High	Low
Operational Cost	No subscription	No subscription	No subscription	No subscription	Subscription-based	Subscription-based
Deployment Cost	Low–Moderate	Low	Low	Moderate	High	Low
Suitability for Agriculture	Large farms, long-range sensing	Greenhouses, short range	Wearable/close-range sensors	High-speed local control	Wide-area reliable sensing	Low-power, sparse monitoring
Overall Suitability Index	High	Medium	Medium	Medium–High	High	Medium

Table 2: Comparative performance metrics of wireless communication protocols for smart agriculture IoT Systems.

V. CONCLUSION

This study systematically evaluated multiple wireless communication protocols—LoRaWAN, NB-IoT, Zigbee, BLE, Wi-Fi, and Sigfox—based on their range, power consumption, latency, packet delivery ratio, cost, and overall suitability for smart agriculture applications. The experimental results clearly indicate that LoRaWAN offers the best overall performance for large-scale agricultural deployments due to its long communication range, low power profile, and stable PDR under varying weather conditions. NB-IoT demonstrates strong reliability and low latency, making it suitable for mission-critical scenarios but at the cost of higher power consumption and recurring network charges. Short-range protocols such as Zigbee and BLE show promise for greenhouse monitoring and localized node clusters but are unsuitable for large fields due to limited coverage.

Wi-Fi, while offering high throughput, presents substantial energy demands and reduced outdoor reliability. The suitability index confirms that no single protocol excels in all metrics, and optimal selection depends heavily on field size, energy availability, sensor density, and desired data upload frequency. Overall, the results highlight that hybrid multi-protocol architectures may provide the most efficient solution for next-generation smart agriculture IoT systems.

VI. FUTURE ENHANCEMENT

Future research can extend this analysis by incorporating real-time adaptive protocol switching, where sensor nodes dynamically choose communication standards based on channel quality, battery level, or data priority. Expanding the study to include emerging communication systems such as 6G-based NTN (Non-Terrestrial Networks) and Low-Power Wi-Fi HaLow could provide deeper insights into next-generation farm automation. Additionally, long-term field trials across multiple crop seasons would allow performance assessment under extreme environmental variations, including monsoon cycles and prolonged drought conditions. Integration of edge AI models for anomaly detection, animal intrusion prediction, and autonomous irrigation recommendations presents another promising direction. Finally, developing a cost–benefit optimization framework that automatically selects the ideal protocol based on field parameters, sensor requirements, and budget constraints can significantly enhance the scalability and practical deployment of smart agriculture IoT ecosystems.

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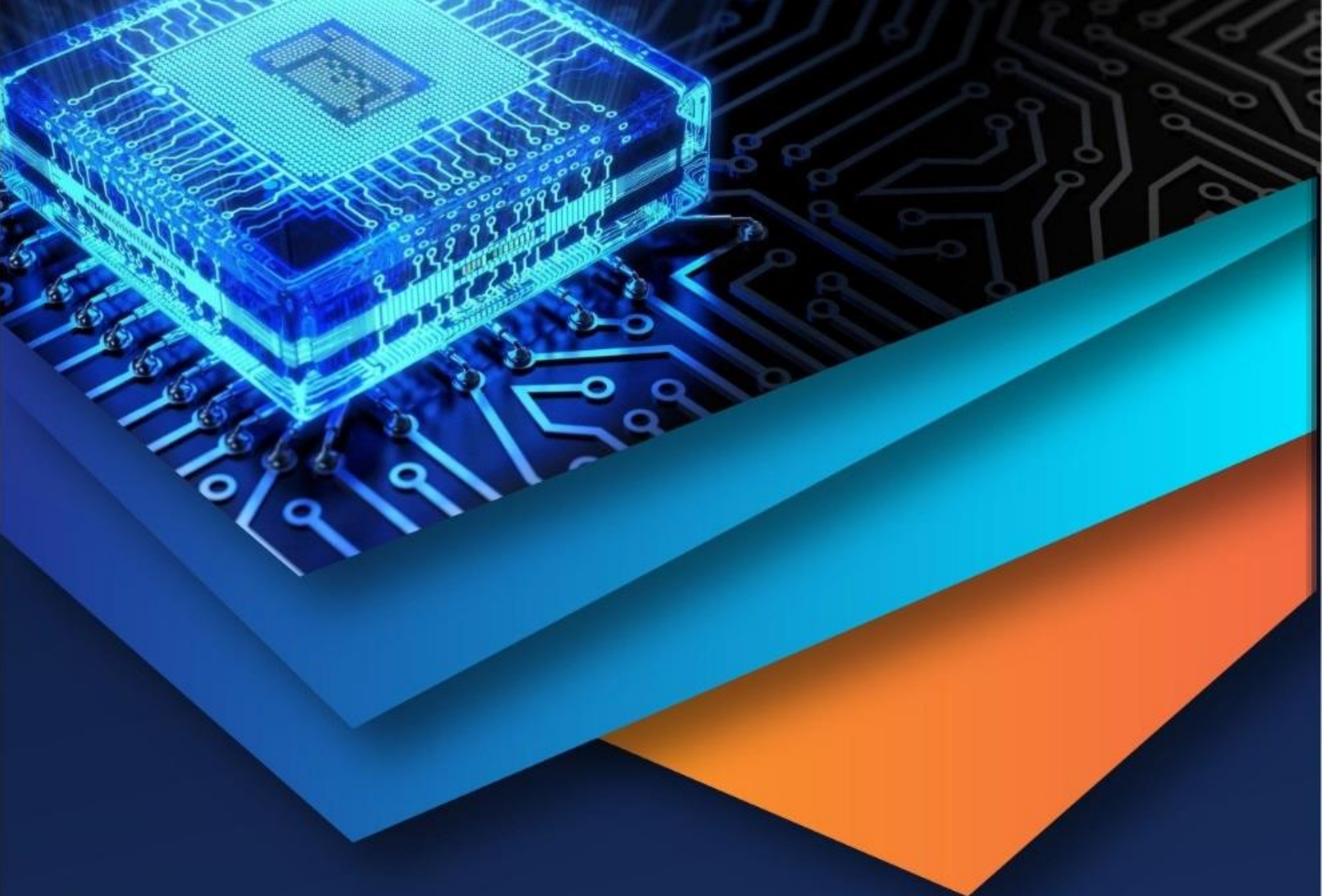

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