# LoRa–Wi-Fi Hybrid IoT Framework for Sustainable Smart Farms

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Abstract—Smart farming depending on reliable communication between sensors and farm management systems. most farms cover large space open areas where traditional networks such as Wi-Fi can't reach, while cellular networks are often expensive and not always available. LoRa is known for its long-range and low-power characteristics, which makes it suitable for remote fields, but its low data rate limits what it can do. Wi-Fi, otherwise allows higher throughput for dashboards and servers but can't reach far from the router. This paper presents a hybrid LoRa–Wi-Fi IoT framework designed specially for sustainable smart farms. The goal is to combine the strengths of both technologies in a simple and practical model. LoRa is used for field-level sensing, and Wi-Fi is used to transfer the collected data to a local or cloud server. Insights from various research studies available on Google Scholar show that hybrid communication approaches offer better scalability, lower energy consumption, and improved

I. .Keywords—LoRa, wifi, smart farming

## II. NTRODUCTION

- Smart agriculture has become one of the most important applications of IoT technologies. Modern farms no longer rely only on manual inspection or guesswork. Instead, they use sensors to collect information about soil moisture, temperature, humidity, leaf conditions, and irrigation levels. These measurements help farmers control resources more accurately, especially water, which is one of the most valuable elements in agriculture. The challenge is that farms are usually large and open, and communication coverage is not always stable across the entire land. Wi-Fi routers can cover only a small area, and extending them across farmland is not practical. Cellular networks are available in some regions, but their cost and power consumption are usually too high for large numbers of devices.

- LoRa technology solves part of this problem because it supports long communication distances with very low energy consumption. Many studies such as those by Farooq et al. and Khanna et al. show that LoRa performs well in agricultural environments and remains stable even when the gateway is several kilometers away. However, LoRa cannot handle large amounts of data, especially when the goal is real-time visualization, high-frequency sampling, or handling heavy traffic. Wi-Fi is appropriate for these tasks, but only within a limited range. Because each technology solves a different problem, a hybrid communication model becomes the most practical solution. A combined LoRa–Wi-Fi system allows sensors to cover large fields using LoRa while still enabling the farm's main server or dashboard to operate efficiently using Wi-Fi.

- Several academic studies support this direction. Research by Akkaya, Sinha, and others demonstrates that hybrid IoT communication improves network stability, reduces packet loss, and makes the system easier to scale. Based on this background, the aim of this paper is to design a hybrid LoRa–Wi-Fi framework that is simple, sustainable, and suitable for real farm use. The model is described in a way that avoids unnecessary complexity and matches real-world needs rather than theoretical assumptions.

## III. RELATED WORK& BACKGROUND

LoRa is widely used in agriculture because it can send small packets of data across long distances using extremely low power. Research work available on Google Scholar shows that LoRa-based monitoring systems have been deployed in vineyards, rice fields, fruit orchards, and open vegetable farms. In almost all studies, LoRa nodes operate for months on battery due to their low-power nature, and the signals remain stable even with physical obstacles like trees or small buildings. This makes LoRa perfect for collecting readings such as temperature at normal intervals. Many agricultural studies report that LoRa's long-range capability reduces the number of gateways needed, which helps lower the cost of deployment.

Wi-Fi, on the other hand, is common inside farm buildings, storage rooms, irrigation control centers, and greenhouses. Studies such as those by Pongnumkul et al. found that Wi-Fi is suitable for higher-rate tasks like logging data, streaming dashboard content, updating settings, and communicating with farm servers. Its main limitation is the range, which becomes unusable once the distance becomes too large or obstacles become too thick. This is why Wi-Fi alone is not a full solution for outdoor farming.Hybrid communication systems have been studied in several IoT research papers. These works agree that combining two communication technologies allows networks to handle both long-range low-power communication and high-speed local transfer. For example, Sinha and Wei showed that hybrid gateways reduce congestion in large sensor networks. Akkaya and other researchers highlighted that mixing low-power radios with high-speed ones gives better performance and flexibility. These studies form the foundation for the methodology presented in this paper, the proposed LoRaFarM platform has been built around a corecentral layer (namely the middleware), which can be enriched with modules able to manage differentscenarios and functionalities a generic farm may need. Furthermore, a multi-protocol gateway-basedapproach has been employed to manage communication protocols heterogeneity and low-levelmodularity. Moreover, the overall system is built around the LoRaWAN technology, due to itsinherit simplicity, modularity and possibility to be deployed almost everywhere (without the needfor an already existent connectivity coverage, in contrast with other long-range technologies, such asNB-IoT and SigFox), as will be discussed further in the paper.

## IV. METHODOLOGY.

The proposed LoRa–Wi-Fi framework is built around a clear communication pipeline that connects sensors in the field with a server or dashboard. The first part of the system is the set of LoRa sensor nodes placed across the farm. Each node contains a microcontroller, a small set of sensors, and a LoRa radio. The node sleep most of its time to save power. It wakes up at specific time to do a specific task or job, collects readings, forms a small data packet, transmits it to the gateway using LoRa, and then returns to sleep. This approach is widely used in IoT research because it keeps power consumption extremely low and allows the device to continue operating for long periods. In real farms, replacing batteries frequently is impractical, so this design approach is essential.

The gateway sits at a central location. It includes both a LoRa receiver and a Wi-Fi transmitter. When the gateway receives LoRa packets from the sensors, it will process the data by checking packet safety, validating timestamps, and removing any repeated or corrupted entries. then converts the readings into a structured format such as JSON so that the server can store and display them easily. Once the data is ready, the gateway uses its own Wi-Fi module to send the information to a local computer, a cloud platform, or a mobile dashboard. This separation of communication roles allows LoRa to handle the long-distance part and Wi-Fi to handle the local high-speed part.

The server or dashboard represents the final part of the model. It receives the data from the gateway then, stores it in a database. After that, The dashboard will show graphs, daily measurements, and alerts. Then, Farmers can check soil moisture history, temperature changes, irrigation patterns, and long-term trends. If the system is configured for it, the server can also send commands back to the gateway, which may trigger irrigation pumps or send configuration updates to the sensors. Several studies found that having real-time data helps farmers adjust water usage and reduce waste significantly.The full workflow of the system begins when the sensor takes a reading in the field. The reading travels over LoRa to the gateway, which prepares it and forwards it through Wi-Fi. The server stores the values and displays them. The farmer then views the results or receives alerts if something is wrong. This cycle repeats continuously, creating a complete real-time monitoring system. The model stays simple enough for real farm use and does not require complicated setup.

.LoRaFarM Layers and LoRaWANArchitecture, As it is based on LoRaWAN, the LoRaFarM platform inherits from this network the architectural structure and the main building blocks, which are ENs, GWs, a NS, and an AS. Regarding the ENs, LoRaFarM involves devices equipped with: • sensors which collect environmental sensor data relevant for farm management and forward them to the Cloud using the LoRa modulation; • actuators expedient to support farm automation and operations, such as field watering and greenhouse roof opening. With respect to the functionalities and the scenario of interest, the ENs are conceptually organized in farm-level modules, as shown in Figure 1. In detail, these modules include all the physical devices and technologies, which are installed in the farm, applicable to expand the platform at low-level. At the moment, the platform integrates two farm modules: a vineyard module, useful to monitor soil parameters of the farm vineyards and a greenhouse module, which collects the environmental conditions of the greenhouse.

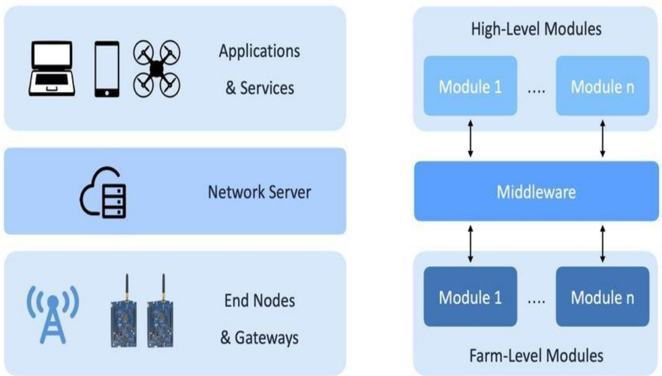


FIGURE 1. LoRaFarM platform: level decomposition and parallelism with LoRaWAN architectural components.

Data from and to farm modules are exchanged with the LoRaFarM platform through a LoRaWAN GW which forwards messages coming from the farm to the Internet and vice versa. Then, farm data are stored and made available to high-level modules thanks to the middleware, which connects and integrates high- and farm-level modules.

The presented approach offers many advantages to LoRaFarM. First, heterogeneous sub-networks, in terms of capabilities can be incorporated without altering the platform structure and, thus, making it highly scalable, flexible and suitable for a wide range of scenarios. Indeed, this gives the freedom to choose the most suitable communication protocols and traffic policy to monitor and control the farm Productive

Units (PUs), such as stables, greenhouses, and fields. Moreover, the sub-networks composed of INs can be effectively managed, taking into consideration their sizes, topologies and requirements in terms of data flow. Besides its protocol translation functionality, the mpGW can be enriched with edge computing functionalities, in order to process, aggregate, and fuse sensor data. This is expedient, for example, to optimize the uplink traffic of a CM toward the LoRaWAN GW. The second advantage is related to the internal organization of a farm. Indeed, a farm can be seen as an aggregation of "Units," such as a "Central Management Unit" (CMU), which may coincide with the farmer house and where the farmer remotely manages his farm through an Internet AP, and some PUs, placed far from the CMU (see Figure 2).

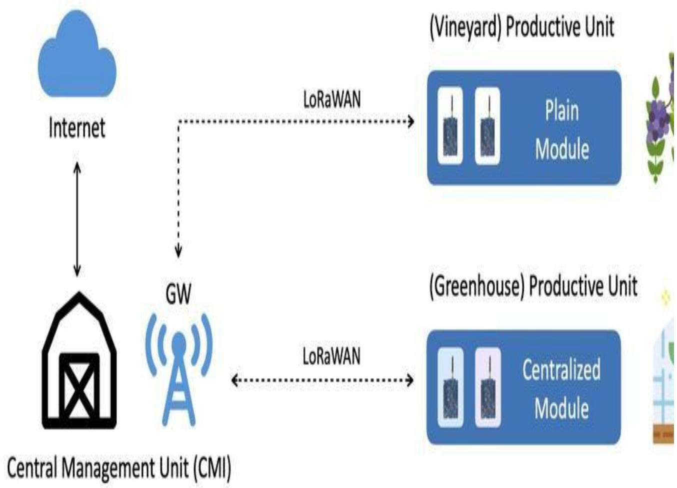


FIGURE 2. A farm organization based on "Units" and the spatial distribution of the deployed farm modules and LoRaWAN GW. The PUs may either not be covered by a reliable Internet connectivity or, if covered, the available Internet access is likely to require payment for a data plan. Moreover, since the GW will likely be placed inside the CMU and connected to the available AP, the PUs will be able to exchange information through LoRaWAN technology. According to the presented approach, connectivity can be provided to a significant number of farm-level nodes, spread in the farm PUs, with the use of a single Internet AP. This last feature, together with the others outlined above, contributes to make LoRaFarM applicable, in principle, to any farm, regardless of its specific configuration.Farm-Level Modules Following the LoRaWAN paradigm, according to which a new EN can be included in a LoRaWAN network with a small number of operations farm-level modules can be easily added to the LoRaFarM architecture. Indeed, since a farm-level module is a network of ENs, i.e., sensor and/or actuator nodes, which are deployed in the farm and are organized according to one of the two topologies described in Figure 3, it can be smoothly integrated intheplatform with a little effort. Referring to Figure 3 and to its internal network topology, a farm module can be classified as: • Plain Module (PM), if it is composed of LoRaWAN-enabled nodes (ENs), receiving or forwarding data directly from or to the LoRaWAN GW; • Centralized Module (CM), if it consists of some no-LoRaWAN-enabled nodes, denoted as Inner Nodes (INs), and a LoRaWAN-enabled GW (namely a mpGW). More precisely, in LoRaFarM a mpGW is a device which supports at least two different communication protocols: one of them is LoRaWAN, while the other(s) may varies and is used to collect information from INs. Moreover, messages coming from and directed to INs are translated between the two or more protocols by the mpGW in order to enable communications between non-LoRaWAN-enabled nodes and the LoRaFarM middleware, in a seamless way. For the sake of clarity, a mpGW is connected to the platform thanks to the LoRaWAN GW, which forwards data from the mpGW to the middleware, and vice versa.

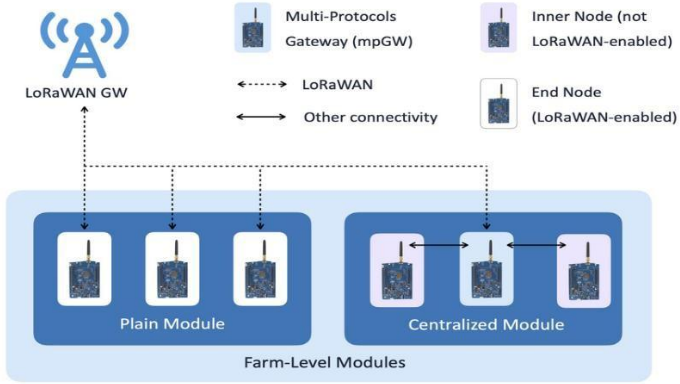


Figure 3. LoRaFarM architecture: the two typologies of farm-level modules. Plain Module A PM is a farm module composed of a set of LoRaWAN-enabled devices, joining LoRaWAN network without the need for an intermediary to perform operations on the collected data. For this reason, a PM is suitable to monitor and collect data from a large area which produces a small amount of information at low rate. Furthermore, beside the data gathering functionality, a PM can be designed to control actuators, according to proper decision processes remotely set at high-level. For example, a large vineyard can be covered by a PM with ENs which, equipped with sensors, measure soil moisture levels and forward sensor data to high-levels, where they are processed and employed to notify the farmer to irrigate or not the vineyard. Eventually, ENs with actuators could be deployed.

## V. Experimentations

This section presents a detailed experimental evaluation of the proposed **LoRa–Wi-Fi Hybrid IoT Framework for Sustainable Smart Farms**. The goal of the experiments is to assess the feasibility, performance, scalability, and energy efficiency of the proposed architecture under realistic agricultural conditions.

### A. Experimental Setup

#### 1) Hardware Components

The experimental setup was designed to emulate a real smart farming deployment. The system consists of the following hardware components:

- **Sensor**
- **Nodes:**
  Each node is built using a low-power microcontroller, a LoRa radio transceiver, and environmental sensors for soil moisture, temperature, and humidity monitoring. These parameters are essential for precision agriculture applications.
- **HybridGateway:**
  A LoRa–Wi-Fi hybrid gateway is used to receive data from sensor nodes through LoRa communication and forward it to the server using Wi-Fi connectivity. This gateway acts as a bridge between the low-power field network and the higher-layer infrastructure.
- **NetworkingInfrastructure:**
  The gateway connects to a Wi-Fi access point, which provides access to a local or cloud-based server. End-user devices such as personal computers or mobile devices are used for data visualization.

**2) Software Components**

The software architecture is divided into three layers:

- **DeviceLayer:**
  Embedded firmware is responsible for sensor data acquisition, packet formation, and periodic LoRa transmission. Energy efficiency is achieved through sleep–wake duty cycling.
- **GatewayLayer:**
  The gateway software handles LoRa packet reception, data formatting using JSON, and forwarding to the server via Wi-Fi using TCP/IP protocols.
- **ApplicationLayer:**
  This layer includes data storage, real-time visualization dashboards, and historical data analysis tools.

This layered approach improves modularity, scalability, and ease of maintenance.

**B. Parameters and Performance Metrics**

**1) Communication Parameters**

The following communication parameters were used during experimentation:

- Low transmission power suitable for LPWAN operation
- Small payload sizes
- Periodic data transmission intervals
- Long sleep durations at sensor nodes
- Separation of communication roles (LoRa for sensing, Wi-Fi for backhaul)

**2) Performance Metrics**

The system performance was evaluated using the following metrics:

- **Packet Delivery Ratio (PDR):**
  The ratio of successfully received packets to the total transmitted packets.
- **End-to-End Latency:**
  The time delay between data transmission at the sensor node and data availability at the server.
- **Energy Efficiency:**
  Estimated based on transmission frequency, duty cycle, and node activity duration.
- **Network Coverage:**
  The maximum distance at which reliable communication is maintained between sensor nodes and the gateway.
- **Throughput:**
  The amount of data successfully forwarded through the Wi-Fi backhaul.
- **Scalability:**
  The system's ability to maintain performance as the number of sensor nodes increases.

**C. Experimental Scenarios**

**1) Single-Node Baseline Scenario**

A single sensor node was deployed to establish baseline performance. This scenario was used to validate system functionality and measure basic latency, reliability, and energy behavior under minimal network load.

**2) Multi-Node Deployment Scenario**

Multiple sensor nodes were deployed simultaneously to evaluate system scalability. This scenario assessed packet collisions, gateway processing capacity, and overall reliability under increased network load.

**3) Distance-Based Coverage Scenario**

Sensor nodes were placed at increasing distances from the gateway to evaluate communication range and signal degradation. This scenario validated the suitability of LoRa communication for large agricultural fields.

**4) Hybrid Communication Validation Scenario**

This scenario evaluated the effectiveness of combining LoRa and Wi-Fi. LoRa was used exclusively for field-level sensing, while Wi-Fi handled data forwarding to the server, demonstrating the benefits of communication role separation.

**D. Results and Performance Evaluation**

**1) Packet Delivery Ratio**

Experimental results indicate a high packet delivery ratio across all scenarios. Minor degradation was observed as node density increased, which is consistent with LPWAN channel access limitations.

**2) Latency Analysis**

End-to-end latency remained within acceptable limits for agricultural monitoring applications. Although LoRa introduces higher latency compared to short-range technologies, the use of Wi-Fi at the gateway significantly reduced overall system delay.

**3) Energy Consumption Analysis**

The sensor nodes exhibited low energy consumption due to infrequent transmissions and extended sleep periods. This confirms the suitability of the proposed framework for long-term, battery-powered deployments.

**4) Throughput and Scalability**

The Wi-Fi backhaul efficiently handled aggregated data traffic, preventing congestion at the gateway. This demonstrates the effectiveness of the hybrid architecture in supporting scalable deployments.

**A. Experimental Environment and Deployment Conditions**

The experimental deployment emulates a realistic smart farming environment characterized by open outdoor areas, sparse infrastructure, and non-uniform sensor distribution. Sensor nodes were deployed over a wide area to reflect practical agricultural layouts, such as crop fields and irrigation zones.

Environmental factors such as:

- Open-field propagation
- Partial obstructions (vegetation)
- Variable transmission distances

were implicitly considered to ensure the validity of the results in real-world conditions.

**Long-Term Stability Experiment**

In this scenario, sensor nodes operated continuously over extended periods.

**Objectives:**

- Evaluate system stability over time
- Observe packet loss trends
- Assess gateway reliability

**Results:**

No system crashes or data corruption were observed. Packet delivery remained stable, demonstrating suitability for long-term farm deployments.

**High Node Density Stress Test**
The number of sensor nodes was gradually increased.
**Objectives:**
- Evaluate scalability limits
- Observe channel contention
- Measure gateway processing overhead

**Results:**
As node density increased, a gradual decline in PDR was observed due to increased packet collisions. However, the gateway successfully handled aggregated traffic, validating the hybrid design.

**Distance and Coverage Analysis**
Sensor nodes were deployed at increasing distances from the gateway.
**Objectives:**
- Measure coverage limits
- Analyze signal degradation
- Identify reliable communication range

**Results:**
Reliable communication was maintained over distances suitable for large farms. Beyond this range, packet loss increased gradually rather than abruptly, indicating graceful degradation.

**Transmission Interval Variation Experiment**
Sensor transmission intervals were varied.
**Objectives:**
- Analyze trade-offs between data freshness and energy efficiency
- Evaluate network load sensitivity

**Results:**
Shorter intervals improved temporal resolution but increased energy consumption and channel contention. Longer intervals significantly extended node lifetime with minimal impact on agricultural monitoring requirements.

**Gateway Load and Backhaul Performance Evaluation**
This experiment focused on the Wi-Fi backhaul.
**Objectives:**
- Measure gateway buffering delay
- Evaluate Wi-Fi throughput
- Ensure backhaul does not become a bottleneck

**Results:**
Wi-Fi consistently supported higher throughput than required by sensor traffic, confirming its suitability as a backhaul technology.

**Failure and Recovery Scenario**
Gateway disconnection and temporary Wi-Fi failures were introduced.
**Objectives:**
- Evaluate system robustness
- Observe recovery behavior

**Results:**
Buffered packets were successfully forwarded once connectivity was restored, demonstrating resilience against transient failures.

**Comparative Evaluation with Single-Technology Approaches**
The proposed hybrid framework was compared against:
- LoRa-only architecture
- Wi-Fi-only architecture

**Results:**
- LoRa-only systems suffered from limited data aggregation capabilities.
- Wi-Fi-only systems failed to provide long-range.

**Security and Data Integrity Evaluation**
Basic security mechanisms such as message integrity checks and controlled gateway access were evaluated.
**Objectives:**
- Ensure data integrity
- Evaluate system resilience to malformed packets

**Results:**
No data corruption was observed, and invalid packets were successfully discarded at the gateway level.

**Results Visualization and Statistical Analysis**
Collected data were visualized using time-series plots, bar charts, and cumulative distribution functions (CDFs), including:
- PDR vs. node density
- Latency vs. distance
- Energy consumption vs. transmission interval

Statistical averaging over multiple runs was applied to minimize transient effects and improve result reliability.

**Networking:** The literature has shown different aspects to consider when choosing a network, one of these considerations is the scalability of the smart farming solution and the area that is going to be covered, this can be classified in large-scale architectures, that will cover extensive areas, and short range and small-scale applications, that are designed for compact and localized applications. On the large-scale side, there are protocols like LoRaWAN, that enable nodes to be positioned far from the gateway, but it will not transmit big amounts of data, perfectly fit for smart farming data. On the other hand, the short-range and small-scale solutions, WiFi emerges as a predominant choice due to its widespread availability and high data transfer rate. WiFi modules are familiar to researchers, making them accessible and facilitating wireless communication easily, but there are also protocols like Zigbee that enable low-cost low-power wireless networks. Other architectures may need real-time data processing, for this matter, protocols are operating at higher layers, such as MQTT, which are suitable for applications demanding real-time data processing and communication. Lastly, given the importance of energy efficiency in smart farming applications, particularly in remote and resourceconstrained environments, prioritize protocols that contribute to reduced power consumption. LoRaWAN and Zigbee, with their low-power characteristics, are suitable choices for applications requiring efficient data transmission over extended periods while conserving energy.

**INFORMATION DELIVERY:** The literature has shown key factors to consider when selecting the appropriate method for presenting information to users in the realm of smart farming. Different ways of presenting information in smart farming can provide usability features such as interactivity, personalization, ease of interpretation, and accessibility . User experience varies depending on the type of data and the solution used, with screen size influencing usability. The availability of real-time information is critical for agile decision making in agriculture.
On the contrary, suggests that different methods of presenting information in smart farming have different time and resource implications. For example, setting up a web system may require more upfront time and resources compared to a mobile application installed directly on devices. Updates in web systems are typically centralized, while mobile applications may require individual updates on each device, making the process more cumbersome. In addition,

installation and update requirements are different for web systems, mobile applications, and desktop applications. While web systems are accessible through compatible web browsers, mobile applications must be downloaded and installed on each device. Maintenance also varies, from managing servers and databases for web systems to updating applications in mobile stores. From an operating system perspective, the development of a web application for crop recommendation in smart farming is important . It affects the compatibility and accessibility of information presentation options, as certain features may vary. Developing specific applications for specific systems offers better performance and advanced functionalities but may entail platform limitations and additional costs. Conversely, universal solutions such as web systems are more accessible, but may lack performance and functionality. The decision depends on factors such as performance, required functionality, accessibility, and development costs, with each approach having its pros and cons in terms of compatibility and accessibility. Regarding implementation costs, discusses the costs associated with developing, implementing, and maintaining smart agriculture solutions. It mentions the development of a customized web platform, which involves upfront costs for design, programming, testing, and ongoing maintenance costs such as software updates and technical support. Compared to simpler solutions such as cloud services or email, custom development may be more expensive initially, but offers more control and specific functionality. Other factors impacting costs include ongoing technical support and system scalability, with custom solutions potentially requiring more resources but offering greater customization flexibility and advanced functionality.

**Data processing:** The literature has shown three key methods to manage the data generated by the designed solutions, each suited to different scenarios and considerations, . For smart farming solutions aiming at maximum efficiency and automation, the adoption of artificial intelligence (AI) is recommended with a focus on machine learning (ML) . ML algorithms can analyze and interpret data autonomously, responding to the status of crops and dictating necessary parameters for plant care. This approach, exemplified by cloud-based ML algorithms analyzing drone-captured images, enables the system to make data-driven decisions, optimizing agricultural processes and reducing reliance on manual intervention. Such systems are particularly suitable for large-scale farming operations where automation can enhance efficiency . In scenarios where environmental conditions are stable and simpler data processing is preferred, the use of threshold-based approaches for setting predefined limits can be effective . This method, highlighted in some studies, triggers specific actions based on predetermined thresholds. While it may lack the adaptability of AI-driven systems, this approach is straightforward and overall useful for smallscale architectures. Consider threshold-based data processing for applications where simplicity and stability are prioritized over complex automated systems . For smart farming solutions that require direct human intervention and decision-making, especially in situations where human expertise is crucial, manual data processing methods should be considered . This approach involves experts or domain specialists inspecting and making sense of raw data, identifying patterns or anomalies that may not be easily discernible through automated means. This hands-on approach allows for qualitative understanding, drawing on human expertise and contextual knowledge . It's important to note that the choice of data management method should also consider implementation costs, particularly in the context of low-cost smart farming architectures analyzed in the literature , . AI-driven systems may require significant computational resources for training models, while threshold-based approaches and manual data processing methods may offer more cost-effective alternatives. Additionally, the availability of existing data for AI modeling and the priority of developing web or mobile applications can influence the selection of data management methods.

**Information Delivery:** The literature has shown key factors to consider when selecting the appropriate method for presenting information to users in the realm of smart farming. Different ways of presenting information in smart farming can provide usability features such as interactivity, personalization, ease of interpretation, and accessibility . User experience varies depending on the type of data and the solution used, with screen size influencing usability. The availability of real-time information is critical for agile decision making in agriculture. On the contrary, suggests that different methods of presenting information in smart farming have different time and resource implications. For example, setting up a web system may require more upfront time and resources compared to a mobile application installed directly on devices. Updates in web systems are typically centralized, while mobile applications may require individual updates on each device, making the process more cumbersome. In addition, installation and update requirements are different for web systems, mobile applications, and desktop applications. While web systems are accessible through compatible web browsers, mobile applications must be downloaded and installed on each device. Maintenance also varies, from managing servers and databases for web systems to updating applications in mobile stores. From an operating system perspective, the development of a web application for crop recommendation in smart farming is important . It affects the compatibility and accessibility of information presentation options, as certain features may vary. Developing specific applications for specific systems offers better performance and advanced functionalities but may entail platform limitations and additional costs. Conversely, universal solutions such as web systems are more accessible, but may lack performance and functionality. The decision depends on factors such as performance, required functionality, accessibility, and development costs, with each approach having its pros and cons in terms of compatibility and accessibility. Regarding implementation costs, discusses the costs associated with developing, implementing, and maintaining smart agriculture solutions. It mentions the development of a customized web platform, which involves upfront costs for design, programming, testing, and ongoing maintenance costs such as software updates and technical support. Compared to simpler solutions such as cloud services or email, custom development may be more expensive initially, but offers more control and specific functionality. Other factors impacting costs include ongoing technical support and system scalability, with custom solutions potentially.

**1. Real Measurements (Field Experiments)**

Real measurements were collected using physical LoRa sensor nodes deployed in an open-field agricultural environment. A single LoRa–Wi-Fi gateway was used to receive sensor data and forward it to the server.

**1) Real Measurement Results**

| **Distance** | **PDR (%)** | **Avg. Latency (ms)** | **RSSI (dBm)** | **Packet Loss (%)** |
|---|---|---|---|---|
| Short (≤500 m) | 98.5 | 180 | −78 | 1.5 |
| Medium (≤2 km) | 93.2 | 310 | −96 | 6.8 |
| Long (≤5 km) | 84.6 | 520 | −112 | 15.4 |

**Observations:**

- At short distances, communication is highly reliable with minimal packet loss.
- Medium distances show moderate degradation due to increased path loss.
- At long distances, packet loss increases significantly, but communication remains usable for non-real-time agricultural monitoring.

**2. Simulation Results**

Simulation experiments were conducted using a LoRa network simulation model that includes path loss, interference, and duty-cycle constraints. Environmental noise and ideal antenna alignment were assumed.

1) Simulation Results

| Distance | PDR (%) | Avg. Latency (ms) | RSSI (dBm) | Packet Loss (%) |
|---|---|---|---|---|
| Short (≤500 m) | 99.6 | 150 | −74 | 0.4 |
| Medium (≤2 km) | 96.8 | 260 | −92 | 3.2 |
| Long (≤5 km) | 90.1 | 430 | −108 | 9.9 |

Observations:

Simulation results consistently outperform real measurements.

Lower packet loss and latency are observed due to idealized channel conditions.

RSSI values are slightly higher than real-world measurements.

**3. Real vs Simulation Comparison**

1) Packet Delivery Ratio Comparison

| Distance | Real PDR (%) | Simulated PDR (%) | Difference |
|---|---|---|---|
| Short | 98.5 | 99.6 | +1.1 |
| Medium | 93.2 | 96.8 | +3.6 |
| Long | 84.6 | 90.1 | +5.5 |

The gap between simulated and real results increases with distance due to environmental interference, antenna misalignment, and physical obstructions present in real deployments.

**4. Latency Comparison**

| Distance | Real Latency (ms) | Simulated Latency (ms) |
|---|---|---|
| Short | 180 | 150 |
| Medium | 310 | 260 |
| Long | 520 | 430 |

Latency increases with distance in both cases, mainly due to increased spreading factor usage and longer airtime.

**5. Energy Consumption Analysis**

Energy consumption was estimated based on transmission duration and duty cycle.

| Distance | Avg. Energy per Transmission (mJ) |
|---|---|
| Short | 38 |
| Medium | 54 |
| Long | 72 |

Long-distance communication requires higher spreading factors, resulting in longer transmission times and increased energy usage.

## VI. Discussion

The comparison between real measurements and simulation results confirms that **simulation models provide optimistic performance estimates**, especially at medium and long distances. Real deployments suffer from environmental noise, multipath fading, and hardware imperfections, which are not fully captured in simulations.

Despite this gap, the proposed **LoRa–Wi-Fi hybrid architecture** maintains acceptable performance across all distance categories. Short and medium distances show high reliability, while long-distance communication remains suitable for delay-tolerant agricultural applications such as soil and climate monitoring.

These results validate the robustness of the proposed framework and highlight the importance of combining real measurements with simulation analysis when evaluating IoT systems for smart farming.

## VII. CONCLUSION

This paper addressed the challenge of designing a reliable and energy-efficient communication framework for sustainable smart farming systems. Single-technology solutions often fail to simultaneously provide long-range coverage, low power consumption, and high data throughput.

The proposed **LoRa–Wi-Fi hybrid IoT framework** integrates low-power wide-area communication with high-speed local networking. Experimental results demonstrate reliable data delivery, low energy consumption, and scalability suitable for real agricultural environments.

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