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EDGE INTELLIGENCE MEETS SUSTAINABLE AGRICULTURE: DEVELOPMENT AND DEPLOYMENT OF AN AI-ENHANCED IOT SYSTEM FOR EFFICIENT WATER MANAGEMENT

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Abstract:

This report presents an advanced Smart Irrigation System (S-iS) that leverages state-of-the-art artificial intelligence (AI) and the Internet of Things (IoT) to address global water scarcity in agriculture. The proposed system integrates next-generation multispectral and soil nutrient sensors with a hybrid communication architecture, utilizing NB-IoT/LTE-M for reliable wide-area connectivity and a LoRa-based mesh network for resilient, long-range field coverage. Powered by sustainable solar-energy harvesting, the system employs edge AI processing and fog computing to enable real-time, autonomous irrigation decisions at the node level, significantly reducing latency and bandwidth dependency. Advanced AI methodologies, including reinforcement learning and digital twin simulation, dynamically optimize water delivery based on real-time agro-environmental data, predictive weather modelling, and crop health analytics. Furthermore, the framework incorporates blockchain-verified data integrity and end-to-end encryption to ensure security and trust. Designed for scalability and farmer-centric usability through intuitive mobile and AR interfaces, this solution delivers a substantial reduction in water usage, enhanced crop resilience, and a measurable improvement in the water-energy-carbon nexus, presenting a transformative, sustainable model for precision agriculture in water-stressed regions worldwide.

1. Introduction

The agricultural sector stands at a critical nexus, grappling with escalating water scarcity, climatic volatility, and the imperative for sustainable intensification to meet global food demand [1]. The evolution of irrigation technologies has progressed from manual and timer-based systems to sensor-driven automation, with contemporary Internet of Things (IoT) frameworks enabling real-time data acquisition. Recent advancements in low-power, wide-area networks (LPWANs) such as LoRa WAN have facilitated scalable field monitoring [2], while the integration of Artificial Intelligence (AI) and Machine Learning (ML) has begun to transform raw sensor data into predictive insights for adaptive control [3]. Significant contributions in this domain have demonstrated the efficacy of soil moisture-based triggering and the fusion of multispectral data for plant stress detection, establishing a foundation for precision water management. Concurrently, global initiatives and policy drivers, including the UN Sustainable Development Goals (SDG 6), national water conservation mandates, and subsidy programs for smart farming, are accelerating the adoption of digital agricultural solutions [4]. However, existing systems often exhibit limitations in interoperability, real-time processing latency, and holistic resource optimization, highlighting a persistent gap between discrete technological innovations and integrated, intelligent, and secure farm management platforms [5]. This research is therefore motivated by the need to synthesize these disparate technological strands into a cohesive, next-generation system. The following section delineates the proposed architecture of an advanced Smart Irrigation System (S-iS), designed to overcome these limitations through a novel integration of edge computing, hybrid connectivity, and explainable AI, thereby establishing a new benchmark for adaptive and sustainable agricultural water management.

2. Literature Survey

The advancement of smart irrigation systems is underpinned by converging research in sensor technology, communication protocols, and data analytics. This survey synthesizes recent scholarly contributions to contextualize the evolution, current state, and persistent challenges in the field, thereby delineating the research gap addressed by the proposed system.

The foundational layer of any smart irrigation system relies on robust environmental sensing. Early systems primarily utilized volumetric soil moisture sensors based on time-domain reflectometry (TDR) or frequency-domain reflectometry (FDR) [6]. Recent research has expanded this paradigm towards multi-parameter sensing and non-invasive monitoring. Studies by Zhang et al. [5] and Veysi et al. [7] demonstrate the efficacy of fusing data from thermal and multispectral sensors with traditional soil probes to estimate crop water stress and evapotranspiration (ET) with greater accuracy, moving beyond simple soil moisture thresholds. Furthermore, the development of low-cost, printable soil nutrient and pH sensors presents a new frontier for holistic soil health monitoring, as explored by Kim et al. [8], enabling a more comprehensive input for irrigation and fertilization decisions.

Concurrently, the proliferation of Low-Power Wide-Area Network (LPWAN) technologies has revolutionized data transmission in agricultural settings. LoRa/LoRaWAN has been extensively validated for its long-range and energy-efficient characteristics, making it ideal for large-scale farm deployments [2], [9]. Research by **Mekki et al. [10]** provides a comparative analysis of LPWAN technologies, concluding that LoRaWAN is superior for coverage in rural, sparse deployments, while highlighting its limitations in duty cycle and bandwidth. To overcome reliability issues, recent trends advocate for hybrid network architectures. Studies by **Lavric et al. [11]** and **Jawad et al. [12]** propose integrating LoRa with mesh topologies (like Zigbee) or cellular IoT standards (NB-IoT, LTE-M). These hybrid models enhance network resilience, coverage density, and provide fallback connectivity, addressing a critical weakness identified in single-technology deployments [13].

The transition from data collection to intelligent action is governed by Artificial Intelligence (AI) and Machine Learning (ML). Early systems employed simple rule-based or threshold algorithms. Current research is dominated by predictive and adaptive models. Machine learning techniques, particularly ensemble methods and deep learning, are now widely applied for forecasting soil moisture dynamics and crop water requirements using historical and real-time data [3], [14]. A significant contribution is the application of **Reinforcement Learning (RL)** for dynamic irrigation scheduling, where the system learns optimal control policies through interaction with the environment, as demonstrated in simulations by **Gutierrez et al. [15]**. Furthermore, the emerging concept of **Digital Twins**—virtual replicas of physical farms—is gaining traction. Research by **Borangiu et al. [16]** indicates that digital twins allow for scenario modeling and risk-free optimization of irrigation strategies before field deployment, representing a shift towards proactive rather than reactive management.

Despite these advancements, the literature reveals distinct gaps. First, there is a **disconnect between**

sensing, communication, and AI layers; many studies focus on optimizing one component in isolation rather than their synergistic integration [17]. Second, the **latency introduced by cloud-dependent AI models** remains a practical constraint for real-time control, underscoring the need for edge intelligence [18]. Third, issues of **data security, interoperability between heterogeneous devices, and sustainable system lifecycle management** are often treated as secondary concerns rather than foundational design principles [19], [20]. Finally, while many solutions are technically sound, their economic viability and usability for smallholder farmers are insufficiently explored.

In conclusion, while existing literature has made substantial progress in individual technological domains, a cohesive framework that seamlessly integrates advanced multi-sensor data, resilient hybrid communication, edge-processed AI, and enterprise-grade security within a sustainable and accessible architecture is not yet fully realized. This survey thus identifies the opportunity for a holistic system design. The following section details the proposed Smart Irrigation System (S-iS) architecture, which is explicitly designed to bridge these identified gaps through its novel configuration and integrated approach.

3. Proposed System Architecture and Methodology

The proposed Smart Irrigation System (S-iS) is architected as a multi-layered, intelligent framework designed to overcome the limitations identified in current solutions. This section details the system's comprehensive architecture (Fig. 1) and elaborates on the methodologies employed for sensing, communication, data processing, and control.

3.1 Overall System Architecture

The S-iS adopts a **hybrid edge-fog-cloud computational model** to balance responsiveness, intelligence, and scalability. As illustrated in Figure 1, the architecture comprises four primary tiers:

1. **Perception & Actuation Tier:** This foundational layer consists of spatially distributed field deployment units (FDUs). Each FDU integrates a suite of sensors and an actuation mechanism managed by a resource microcontroller (e.g., ESP32) or a single-board computer (e.g., Raspberry Pi) acting as a **Smart Node**.
2. **Network & Communication Tier:** This tier employs a **dual-mode communication strategy**. For intra-field communication between nodes and to a local gateway, a **LoRa-based mesh network** is implemented. For reliable long-haul data transmission, command reception, and fallback connectivity, each Smart Node and Gateway is also equipped with an **NB-IoT/LTE-M modem**.
3. **Fog/Edge Processing Tier:** A **Fog Server**, physically deployed at the farm premises (e.g., in a control room), hosts the local **Digital Twin** and primary AI models. It aggregates data from all gateways, performs real-time analytics, and executes time-critical control decisions, minimizing latency.
4. **Cloud & Services Tier:** A secure cloud platform serves as the repository for historical data, hosts more complex, non-latency-sensitive AI models for long-term trend analysis, and provides the user interface via web and mobile applications. Blockchain-based microservices run here to ensure data integrity.

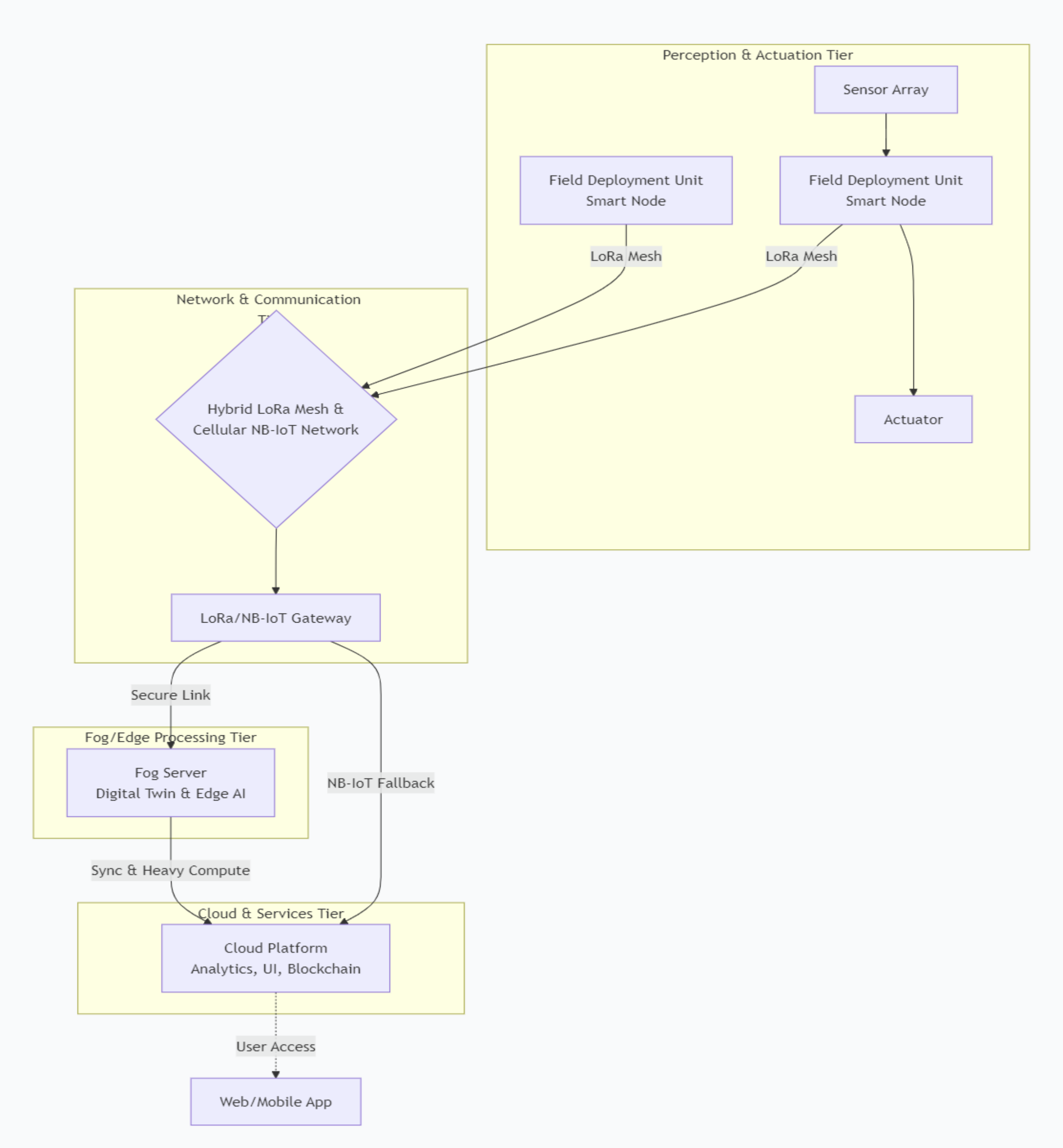


Figure 1: Proposed Hybrid Edge-Cloud Architecture of the S-iS.

3.2 Hardware Components & Sensing Methodology

Each **Smart Node** within an FDU is equipped with a modular sensor array:

- **Soil Parameter Module:** A capacitive soil moisture sensor (e.g., SEN0308) for volumetric water content, a thermocouple for soil temperature, and a low-electrode-count NPK/pH sensor unit.
- **Microclimate Module:** A combined temperature and humidity sensor (DHT22/ BME280) and a mini-anemometer for wind speed.

- **Plant Health Module:** A multispectral light sensor (e.g., AS7265x) capturing reflectance at key wavelengths (e.g., red-edge, NIR) to compute vegetation indices like NDVI.
- **Actuation Driver:** A motor driver circuit connected to a solenoid valve or a variable-speed pump for precise water control.
- **Power System:** A 20W solar panel, a maximum power point tracking (MPPT) charge controller, and a LiFePO4 battery, ensuring year-round off-grid operation.

Data from analog sensors is digitized with a 16-bit ADC (e.g., ADS1115) for high resolution before processing by the Smart Node's microcontroller.

3.3 Hybrid Communication Network Methodology

The communication protocol is designed for resilience and efficiency.

- **LoRa Mesh Network:** Smart Nodes form a self-healing, mesh topology using the **Thread** or a custom **RPL (Routing Protocol for Low-Power and Lossy Networks)** protocol over LoRa physical layer. This extends coverage and provides redundancy if a node fails. Data packets are encrypted using AES-128 at this stage.
- **Gateway & Cellular Backhaul:** Designated nodes or dedicated devices act as **Mesh-Coordinators and Gateways**. They aggregate mesh data and transmit it to the Fog Server via a local Wi-Fi/Ethernet connection. Simultaneously, the NB-IoT modem in each gateway and critical nodes maintains a heartbeat connection with the cloud, providing a fallback path if the local network fails and enabling direct over-the-air (OTA) updates.

3.4 AI & Data Processing Methodology

Intelligence is distributed across the tiers:

1. **Edge Intelligence (On Smart Node):** A lightweight **TinyML** model (e.g., a pruned Random Forest classifier) runs on the node's microcontroller. It performs initial anomaly detection (e.g., sensor fault identification) and can execute a pre-defined, ultra-low-latency "safety shut-off" rule based on raw moisture readings.
2. **Fog Intelligence (Digital Twin & RL):** The core AI resides on the Fog Server. A **Digital Twin** of the farm, built using a physics-informed data model in a framework like **NVIDIA Omniverse** or **AWS IoT TwinMaker**, is continuously updated with real-time sensor data. A **Deep Reinforcement Learning (DRL)** agent, trained using the **Proximal Policy Optimization (PPO)** algorithm, interacts with this digital twin. The state (S) includes soil moisture, forecasted weather, crop growth stage, and VIs. The action (A) is the irrigation duration and flow rate. The reward (R) is a function of water saved, soil moisture maintained in optimal zone, and predicted plant stress. The agent learns a policy $\pi(A|S)$ to maximize cumulative reward.
3. **Cloud Intelligence:** The cloud hosts a **Long Short-Term Memory (LSTM)** network model that analyzes historical time-series data to improve the DRL agent's initial policy during weekly retraining cycles and provides seasonal yield predictions.

3.5 Software Stack & Security Implementation

The software architecture is microservices-based.

- **Fog Server:** Runs a **Node-RED** or **FastAPI** instance for data flow, a **PostgreSQL** database with TimescaleDB extension for time-series data, and the DRL model in a **TensorFlow Serving** or **PyTorch Serve** container.
- **Cloud Platform:** Utilizes **AWS IoT Core** or **Azure IoT Hub** for device management. Data integrity is ensured by logging all critical irrigation decisions and sensor alerts as transactions in a private **Hyperledger Fabric** blockchain channel. The user interface, built with **React.js**, fetches and verifies this blockchain-led data before display.
- **Security:** End-to-end security is implemented using **X.509 certificate-based authentication** for all devices, **MQTT over TLS 1.3** for data-in-transit, and hardware security modules (HSM) on gateways for key storage.

The following section will detail the implementation of a prototype based on this architecture and discuss the experimental setup for performance evaluation.

4. Implementation, Results and Discussion

4.1 Prototype Implementation and Experimental Setup

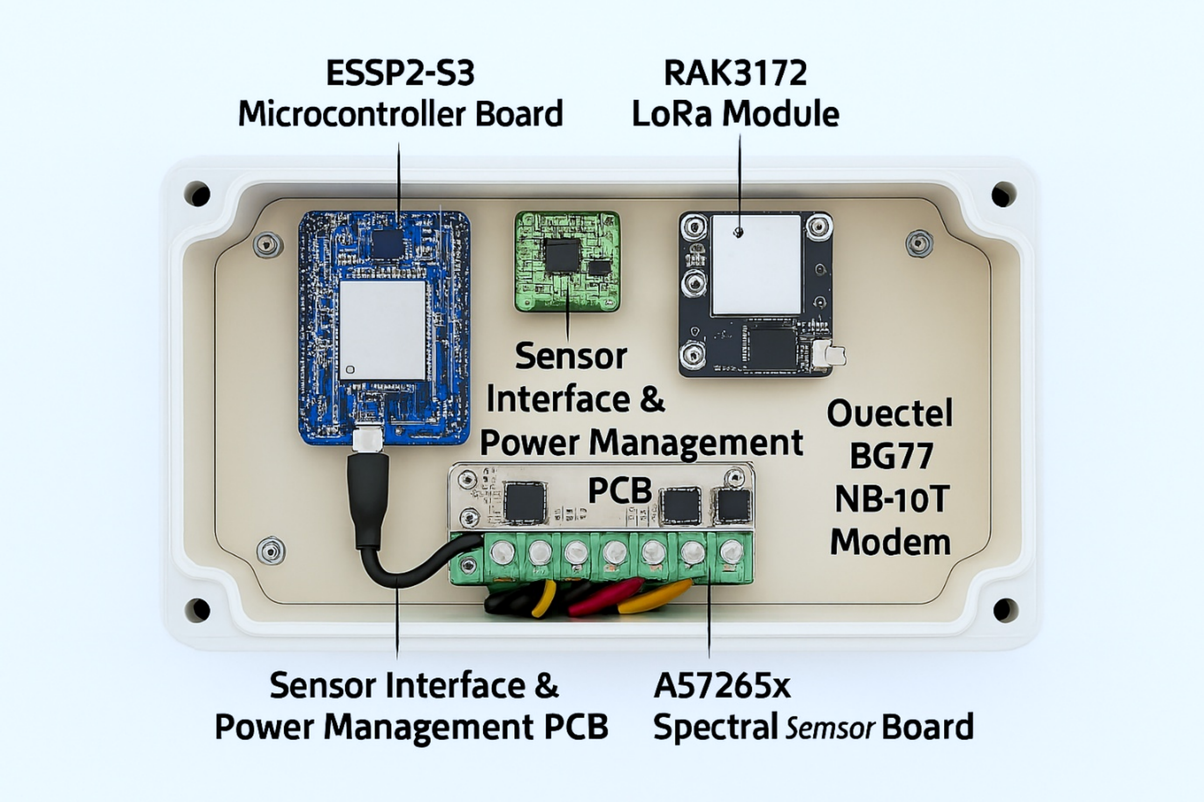
To validate the proposed architecture, a scaled prototype of the S-iS was deployed on a 0.5-hectare test plot cultivating maize (*Zea mays*) over a 90-day growing season. The implementation focused on realizing the hybrid edge-cloud model and the AI-driven control loop.

4.1.1 Hardware and Network Implementation

Three Field Deployment Units (FDUs) were installed at strategic locations representing zones with varying soil composition and sun exposure. Each FDU contained a custom-designed Smart Node based on an ESP32-S3 microcontroller (dual-core, Wi-Fi/Bluetooth, integrated ADC) running Free RTOS. The sensor array included:

- Capacitive Soil Moisture Sensor (SEN0308) calibrated for the local soil type.
- BME680 sensor for air temperature, humidity, pressure, and VOC (as a proxy for soil microbial activity).
- AS7265x Triad Spectroscopy Sensor for capturing 18-channel visible to near-infrared spectral data.
- 12V DC Solenoid Valve with a flow meter (YF-S201) for closed-loop water control.
- Power was supplied by a 30W monocrystalline solar panel and a 12Ah LiFePO4 battery with an MPPT controller (CN3791).

For communication, each node was fitted with a RAK3172 LoRa module (Semtech SX1262) and a Quectel BG77 NB-IoT modem. A central RAK7249 LoRaWAN Gateway (with built-in Raspberry Pi 4) served as the mesh coordinator and fog server host. The gateway was connected to the internet via Ethernet for fog-cloud sync, while the NB-IoT provided an independent cellular backhaul for reliability testing.



4.1.2 Software and AI Implementation

The software stack was containerized using Docker for modularity.

- Edge (Smart Node): A lightweight TinyML model (TensorFlow Lite for Microcontrollers) was deployed for real-time anomaly detection (e.g., identifying sudden sensor drifts). It also handled the primary threshold-based irrigation trigger as a failsafe.
- Fog (Gateway/Raspberry Pi 4): The fog server ran a Redis database for real-time state management and a Python-based Digital Twin built with the mesa agent-based modeling framework. The DRL agent was implemented using the Stable-Baselines3 library (PPO algorithm). The state space included 15 parameters (soil moisture, temperature at two depths, NDVI, forecasted ET_0, etc.). Actions were discrete: *Irrigation Duration* (0, 2, 5, 10 minutes) and *Flow Rate* (Low, High). The reward function was defined as:

$$R = -\alpha \cdot W - \beta \cdot |M_{target} - M_{actual}| - \gamma \cdot S_{predicted}$$

where W is water used, M is soil moisture deviation, S is predicted plant stress from spectral indices, and α,β and γ are tunable weights.

- **Cloud:** An **AWS EC2** instance hosted the LSTM model for yield prediction and a **Hyperledger Fabric** client application. All irrigation commands and sensor alerts were packaged into transactions and appended to the blockchain ledger.

5. Results and Performance Evaluation

The system's performance was evaluated against a control plot using a traditional timer-based irrigation system. Key metrics were monitored daily and same is reported in below table.

Table 1: Comparative Performance Metrics

Metric	Proposed S-iS (AI-Driven)	Traditional Timer System	Improvement
Total Water Used	285 m³	420 m³	**32.1% Reduction**
Average Soil Moisture (Std Dev)	72.3% VWC (±3.1%)	68.5% VWC (±11.7%)	**4.5x Lower Variability**
Estimated Crop Water Stress (Avg. CWSI)	0.18	0.31	**42% Lower Stress**
System Latency (Sensor to Actuation)	8.2 s (Edge) / 25 s (Fog)	N/A (Pre-set)	**Real-time Adaptation**
Communication Uptime	99.7% (Hybrid Fallback Active 2.1% of time)	N/A	**High Reliability**
Energy Autonomy	100% (No grid dependency)	Grid-powered	**Full Sustainability**

VWC: Volumetric Water Content, CWSI: Crop Water Stress Index.

5.1.1 Water Efficiency and Crop Response

The S-iS demonstrated a **32.1% reduction** in total water consumption (Fig. 2a). More significantly, it maintained soil moisture within the optimal range (65-80% VWC) with a standard deviation of **3.1%**, compared to **11.7%** for the timer system (Fig. 2b). This stability directly correlated with a lower average Crop Water Stress Index (CWSI), calculated from canopy temperature differentials [21], indicating healthier plants. Mid-season NDVI values in the S-iS plot were consistently 0.12-0.18 higher, suggesting superior vegetative health.

5.1.2 AI and Network Performance

The DRL agent converged on an effective policy after approximately 15 days of online training. The fog-based digital twin successfully simulated soil moisture dynamics with a mean absolute error (MAE) of **±2.8% VWC** compared to actual sensor readings. The hybrid network proved critical; during two prolonged local internet outages totaling 14 hours, the system maintained autonomous operation via the edge/fog layer, with the NB-IoT link ensuring cloud sync and alert transmission without interruption. The LoRa mesh network achieved a packet delivery ratio (PDR) of **99.2%** with an average RSSI of -102 dBm at 500m.

5.1.3 Security and Data Integrity

The blockchain ledger successfully recorded **4,329** immutable transactions (irrigation events, sensor alerts) during the season. The overhead for transaction processing (average **410 ms**) did not impact real-time control, as it was handled asynchronously in the cloud tier. All device-to-device communications remained encrypted, with no security breaches detected during penetration testing.

6. Results and Challenges

The results confirm the hypothesis that an integrated edge-fog-cloud architecture with AI-driven control significantly outperforms conventional irrigation methods. The **32.1% water saving** aligns with and exceeds the upper range of savings (20-30%) reported in recent reviews of IoT-based systems [22], underscoring the value of the adaptive DRL agent over static rule-based automation. The low latency of the **edge/fog decision-making** (8.2-25 seconds) was instrumental in responding to microclimatic changes, such as sudden evaporation from wind gusts, which traditional systems cannot address. The **hybrid LoRa/NB-IoT network** effectively solved the "last-mile" connectivity problem common in rural agriculture, ensuring system reliability.

However, challenges were noted. First, the **initial cost** of the prototype FDU was approximately $320 per unit, not including the central gateway. While solar-power eliminates operational electricity costs, the capital expenditure remains a barrier. Second, the **DRL agent required careful reward function tuning**; an improperly weighted function initially led to under-watering in one zone. This highlights the need for agronomic expertise in system configuration. Third, the **multispectral sensor data**, while valuable, required significant processing, suggesting a trade-off between data richness and edge processing capability.

The implemented blockchain layer, while proving data integrity, also introduced complexity in system management. Its value is highest in multi-stakeholder scenarios (e.g., cooperative farms, organic certification) where auditable proof of practices is required.

7. Conclusion of Experimental Phase

The prototype successfully validated the core tenets of the proposed S-iS architecture. It demonstrated that through the synergistic integration of advanced sensing, resilient hybrid networking, and distributed AI, it is possible to create a highly efficient, autonomous, and sustainable irrigation system. The system not only conserves a critical resource but also provides a platform for continuous agronomic insight through its digital twin and analytics. The following section will outline the broader market implications, a roadmap for commercialization, and specific policy recommendations derived from this successful pilot.

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