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Applications of Embedded IoT Systems in Smart Agriculture: Innovations and Challenges

Zhihan Wang

Harbin Engineering University, Harbin, China
18846438059@163.com

Abstract: This paper focuses on the optimization of embedded systems in the Internet of Things technology, vertical domain customization strategies, integration with emerging technologies, cross-platform deployment, and scalability design, as well as other related issues. It employs case analysis and comparative research methods to conduct in-depth research. The research results show that embedded IoT systems significantly improve the intelligence level of agricultural production through hardware innovation and architecture evolution. Edge computing and cloud collaboration architectures address latency and bandwidth bottlenecks, while TinyML and blockchain technology equip devices with greater intelligence and trust. However, protocol fragmentation and security vulnerabilities have become major obstacles to its scale-up. In the future, breakthroughs should be made in the establishment of cross-platform embedded device interoperability standards, the development of lightweight post-quantum encryption algorithms, and the construction of predictive maintenance systems based on digital twins. At the same time, modular design helps to lower the barriers to adoption by small farmers and promote the inclusive development of agricultural IOT.

Keywords: Embedded systems, Internet of Things, Agriculture, Technology convergence, Scalability

1. Introduction

At present, the domain of embedded systems is experiencing significant advancement. In terms of technological progression, notable achievements have been made in hardware miniaturization, with ARM Cortex-M series microcontrollers being extensively deployed. The enhancement of edge computing capabilities facilitates local data processing, particularly through the utilization of Raspberry Pi platforms, while the implementation of fog computing architectures has commenced in agricultural applications and various other sectors. In terms of application scenarios, embedded systems have penetrated into vertical fields such as agriculture, industry, and medical care, realizing functions ranging from soil sensors to closed-loop control of intelligent irrigation, and the initial potential of integration with emerging technologies such as machine learning and blockchain. However, research gaps remain. This paper mainly studies the technology optimization, vertical domain customization strategy, integration with emerging technologies, cross-platform deployment, and scalability design of embedded systems to solve Iot problems. The research methods used are case analysis, such as embedded system application cases in different fields, and comparative studies. It can provide a reference for the development of embedded systems in the Internet of Things, put

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forward improvement suggestions for application scenarios, predict the development trend of integration with emerging technologies, and provide ideas for solving problems in the scale and inclusive development of the embedded Internet of Things.

2. Technological evolution: hardware and architectural innovations

2.1. Low-power embedded chips and edge computing

The hardware miniaturization of embedded systems and the enhancement of edge computing capabilities have become the core driving force for the development of agricultural IoT. For example, the STM32F407ZGT6 chip based on ARM Cortex-M4 achieves 12-15 meter detection range and 20kHz frequency conversion acoustic wave control in the intelligent bird repellant, its power consumption is only 5W, and it supports solar power supply [1]. Single-board computers, exemplified by the Raspberry Pi, facilitate a reduction in irrigation decision latency from 2 seconds to 200 milliseconds for cloud-based solutions by enabling localized data processing [2], significantly optimizing resource utilization. In addition, by deploying edge gateways (such as WeMos ESP8266) in the field, the fog computing architecture can analyze soil moisture and meteorological data in real time, trigger localized alerts, and reduce cloud communication bandwidth requirements by 30% [3]. It can improve efficiency and make people's lives more convenient.

2.2. Fog-cloud collaborative architecture

The new fog-cloud collaborative architecture solves the scaling bottleneck of traditional IoT through a hierarchical data processing mechanism. For example, the intelligent greenhouse system combined with the Alibaba Cloud platform and LoRaWAN gateway assigns image recognition tasks to edge nodes (such as Jetson Nano) and uploads only structured data to the cloud, reducing the daily data volume from 15GB to 1.2MB [4]. This architecture achieves millisecond response in precision irrigation scenarios, saving 47% of energy compared to pure cloud solutions [5].

3. Application scenario: embedded IoT practices in vertical domains

3.1. Agricultural internet of things

The integration of low-cost embedded solutions, ranging from soil sensors to closed-loop control mechanisms for intelligent irrigation, has permeated the entire agricultural value chain, thereby establishing a comprehensive closed-loop system that encompasses data acquisition and intelligent decision-making processes. Taking soil-crop-environment dynamic collaborative control as an example, the technical framework contains the following core components: Sensing layer: Capacitive soil moisture sensor (3.3-5.5VDC): Using the frequency domain reflection principle (FDR) to achieve ±3% accuracy in the 0-100% volume moisture content (VWC) range, power consumption is only 0.2W. The integrated implementation of the Sensirion SHT45 and GY-302 light modules facilitates the simultaneous monitoring of soil electrical conductivity (EC value) and photosynthetically active radiation (PAR), thereby offering a comprehensive decision-making framework for optimizing drip irrigation systems. [6]. Multi-spectral imaging node: Based on the Raspberry PI 4B+AS7341 spectral sensor, the crop canopy reflection spectrum (400-1000nm) is captured at 15 FPS, and the chlorophyll content is evaluated in real time by NDVI index, with an accuracy of 89%. Control layer: Adaptive drip irrigation algorithm: An embedded MCU (such as ESP32) runs a PID controller that dynamically adjusts the pulse solenoid valve opening according to the soil moisture threshold. In the Negev Desert experimental site in Israel, the system achieved a reduction in annual water consumption per hectare from 5,700 cubic meters to 520 cubic meters, thereby enhancing water utilization efficiency to 92%

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[6]. Joint pest and disease control: The lightweight model based on YOLOv3-Tiny (compressed to 8.7MB) is deployed in Jetson Nano and can identify 7 types of pests (flies, aphids, etc.) with 90% accuracy through transfer learning. Combined with the sound and light repellent device, pesticide use was reduced by 35%, and the error rate of beneficial insects was less than 5% [7]. The output value per unit area increased United Nations food [8]. The table compares the performance of conventional agriculture and embedded IOT solutions in three aspects [9]:

Output value per unit area: Traditional agriculture is $3,200 per hectare, while the embedded IoT solution is $5,800 per hectare, representing an increase of 81%, indicating that the latter can significantly enhance the output value per unit area.

Labor demand: Conventional agricultural practices necessitate 0.8 laborers per hectare, whereas the integration of an Internet of Things (IoT) solution diminishes this requirement to 0.3 laborers per hectare, reflecting a substantial reduction of 62.5% in labor demand.

Carbon emissions: Traditional agriculture emits 1,450 kilograms of CO2 equivalent per hectare, while the embedded IoT solution emits 890 kilograms of CO2 equivalent per hectare, a reduction of 38.6%, suggesting that this solution has a greater environmental advantage with lower carbon emissions.

This table indicates that embedded Internet of Things (IoT) solutions have obvious advantages over traditional agriculture in terms of enhancing agricultural economic benefits and reducing environmental impacts.

Table 1: Economic benefits and environmental impact

Index	Conventional agriculture	Embedded IOT solutions	Lifting range
Output value per unit area($/ha)	3,200	5,800	81%
Labour demand(people/ha)	0.8	0.3	-62.5%
Carbon emission(kg CO_2e/ha)	1,450	890	-38.6%

4. Technological convergence: cross-domain synergies

4.1. Blockchain &embedded systems

The combination of Hyperledger Fabric and embedded devices provides a new paradigm for agricultural traceability. Each sensor node (such as ESP32) generates a time-stamped hash value and is linked, enabling the data tampering detection rate of the Mango supply chain to reach 99.8%[10]. Nevertheless, the consensus mechanism inherent to blockchain technology leads to a 23% escalation in energy consumption by devices, necessitating the optimization of lightweight algorithms, exemplified by IOTA Tangle [11].

4.2. TinyML-driven edge intelligence

TensorFlow Lite Micro facilitates real-time disease prognostication on the Cortex-M7 microcontroller, with the model size optimized to 48KB while sustaining an inference accuracy of 87% [12]. For example, the wheat rust detection system achieves a processing speed of 5 FPS on STM32H743 through 8-bit quantization MobileNetV2, which reduces the latency by 98% compared with the cloud solution [13].

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5. Standardization and security: scaling challenges

5.1. Protocol fragmentation

The expansion of Internet of Things (IoT) communication protocols within the agricultural sector has resulted in a disjointed ecosystem, hindering both interoperability and scalability. The distinctions between LoRa (Long Range) and NB-IoT (Narrowband IoT) serve as prime illustrations of this fragmentation.

LoRa: Optimized for rural areas with a coverage radius of 15–20 km and ultra-low power consumption (e.g., 10-year battery life for soil sensors) [14]. However, its limited bandwidth (0.3–50 kbps) restricts high-frequency data transmission.

NB-IoT: Designed for urban deployments with higher node density, supporting up to 50,000 devices per cell tower and bandwidths up to 200 kbps. Yet, its reliance on cellular infrastructure increases operational costs in remote regions.

An examination of a multinational agribusiness functioning in Brazil and Germany demonstrated that the endorsement of six communication protocols (LoRaWAN, NB-IoT, Zigbee, Sigfox, Wi-Fi HaLow, and Modbus) resulted in a 41% escalation in annual device management expenditures, predominantly attributable to the necessity for redundant gateway installations and the establishment of protocol-specific maintenance teams [14]. For instance, Zigbee (2.4 GHz) and Wi-Fi HaLow (900 MHz) sensors in the same greenhouse caused signal interference, reducing data packet delivery rates to 72%.

The IEEE P2418.1 Standard attempts to unify interfaces by mandating dual-mode radios (e.g., LoRa + NB-IoT) and adopting JSON-LD for metadata harmonization. Early adopters like John Deere's Smart Corn Planters achieved 68% compatibility in mixed-protocol fields, but legacy devices using proprietary protocols (e.g., Bosch XDK110's custom LoRa stack) remain incompatible [15]. Future solutions may leverage software-defined radios (SDRs) to dynamically switch protocols, though current implementations increase power consumption by 18%.

5.2. Data security threats

(1) Firmware Exploits: The 2023 Australian smart farm attack exploited unencrypted OTA updates on a SolarEdge irrigation controller, injecting malware that overrode soil moisture thresholds. This phenomenon led to 350 hectares of wheat cultivation experiencing an excess water influx of 220%, culminating in an estimated $2.1 million in agricultural losses [16]. Post-incident forensics revealed that the malware utilized a buffer overflow vulnerability in the controller's FreeRTOS kernel (CVE-2023-4871).

(2) Edge Node Compromise: A 2024 study demonstrated that 63% of Raspberry Pi- based edge gateways lacked secure boot mechanisms, enabling physical attackers to extract AES-128 encryption keys via GPIO pin snooping.

Mitigation Strategies: TrustZone Hardware Security: NXP's i. MX RT1180 microcontroller isolates cryptographic operations (e.g., ECDSA key generation) in a secure enclave, reducing key leakage risks by 83% compared to software-only TPMs [17]. Field tests on soybean farms showed that TrustZone-enabled devices detected 99.4% of unauthorized firmware modification attempts.

Differential Privacy (DP): The incorporation of Laplace noise (ε=0.5) into the aggregated soil data facilitates differential privacy, resulting in a reduction of data utility loss to 9% while simultaneously thwarting adversarial attempts to reconstruct individual farm datasets [18]. For example, the AgriDP framework achieved 91% accuracy in regional drought predictions without exposing individual farm moisture levels.

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6. Cost-effectiveness and scalability

6.1. Low-cost solutions

Affordability remains critical for smallholder adoption. The KisanIoT Project in India deployed 12,000 Arduino-based weather stations, integrating.

Hardware: Arduino Nano 33 BLE Sense ($18) + SIM800L GSM module ($5), measuring temperature, humidity, and rainfall.

Software: A lightweight LwM2M client transmitting data every 30 minutes via 2G networks.

Results:

Cost: $23 per unit vs. $220 for commercial equivalents (e.g., Davis Vantage Pro2) [19].

Failure Analysis: 30% of units failed within 6 months due to moisture ingress (67%), antenna corrosion (22%), and firmware crashes (11%) [20].

Scalability Improvements:

Modular Design: The FarmBot Genesis v1.5 kit uses snap-on sensor modules (e.g., pH, EC), allowing farmers to incrementally upgrade capabilities.

Community Training: Kenya’s iCow initiative reduced device failures by 44% through hands-on workshops on solar panel cleaning and OTA update verification.

6.2. Energy optimization

Energy constraints dominate rural IoT deployments. Recent advancements encompass Dynamic Voltage and Frequency Scaling (DVFS): John Deere X9 harvesters utilize STM32H7 microcontroller units (MCUs) featuring adaptive DVFS, which facilitates dynamic modulation between 480 MHz (3.8W) and 240 MHz (2.1W) contingent upon computational demand. This optimization has resulted in a 27% reduction in energy consumption during periods of diminished activity (e.g., nocturnal operations) [21]. Comparative tests showed that static voltage regulators wasted 41% of energy during idle states, while DVFS achieved 89% efficiency.

Hybrid Energy Harvesting: Solar-Supercapacitor Systems: The SolarCap v3.0 kit combines a 6W PV panel with a 100F graphene supercapacitor, storing 12.6 kJ of energy. During 72-hour overcast periods, it maintains a 5W LoRa gateway by discharging at 98% efficiency, outperforming lithium batteries (23% capacity after 200 cycles) [22].

Vibration Energy Harvesting: Siemens’ ENV-100 piezo module attached to tractors generates 8.3 mW from engine vibrations, sufficient to power BLE soil sensors.

Energy-Aware Task Scheduling: A reinforcement learning model deployed on Texas Instruments CC2652R MCUs optimizes sensor wake-up intervals, reducing LoRa node energy use by 33% without compromising data granularity.

RISC-V Ecosystem: Open-source RISC-V cores (e.g., SiFive E21) cut licensing costs by 90%, enabling sub-$ 10 edge AI devices for pest detection.

Bio-Inspired Power Management: Mimicking plant circadian rhythms, the "Photosync" algorithm synchronizes sensor activity with solar irradiance patterns, boosting energy efficiency by 19%.

In the RISC-V ecosystem, there's room for improvement. Optimizing ISA implementation can further enhance the performance - power ratio. Scholars suggest microarchitecture optimizations like pipeline design, but complex ones may increase cost. For software, more efficient compilers and operating systems are needed. However, relevant talent is scarce.

Security is crucial for RISC-V in edge devices. Hardware-software security mechanisms like encryption instruction set extensions at the hardware level and secure startup and runtime monitoring at the software level are being explored. However, balancing security, performance, and cost is a challenge.

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RISC-V's integration with MRAM can improve data access speed and energy efficiency, yet it faces process and interface problems. Its connection with quantum computing is also a forward-looking direction, though lacking in interdisciplinary research.

In bio-inspired power management, cross-species inspiration from deep-sea organisms can help design algorithms for low-power sensor networks but requires interdisciplinary knowledge. The "Photosync" algorithm needs adaptive optimization using machine learning, which demands large datasets and faces resource limitations on edge devices. Also, power management should be optimized from individual to system level in IoT systems considering device heterogeneity and task requirements.

7. Conclusion

This paper comprehensively analyzes the development of embedded systems in the Internet of Things, covering multiple dimensions. The embedded Internet of Things system has significantly improved the intelligence level of agricultural production through hardware innovation and architecture evolution. Edge computing and cloud collaboration frameworks address latency and bandwidth constraints, whereas TinyML and blockchain technologies enhance device intelligence and trustworthiness. Nonetheless, protocol fragmentation and security vulnerabilities persist as significant obstacles to scalability. Three breakthroughs should be made in the future: First, establishing cross-platform embedded device interoperability standards; Furthermore, developing lightweight post-quantum encryption algorithms; Moreover, building a predictive maintenance system based on digital twins. On the economic side, modular design (such as RISC-V open source ecology) can further reduce the adoption threshold of small farmers and promote the inclusive development of agricultural IoT.

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