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Remote Monitoring and Control of Poultry Incubation Parameters Using LoRaWAN for Rural Farm Applications

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Abstract

This study presents the design and evaluation of a LoRaWAN-based remote monitoring and control system for poultry incubation parameters, developed for resource-constrained rural farm settings. Usual IoT monitoring systems rely on Wi-Fi or cellular networks, which are often simply absent or unreliable in those areas, whereas commercial solutions are still too expensive for most small-scale farmers. The proposed system integrates DHT22 temperature and humidity sensors, an Arduino Uno microcontroller control unit using a hysteresis-based ON/OFF logic with a 0.5°C dead band, plus LoRa WAN communication modules working at 868 MHz. The system maintains continuous environmental monitoring in near real time, while automated control happens locally when needed. Data is transmitted to a ThingSpeak cloud-based visualization platform, enabling remote supervision through real-time data display, historical trending, and automated SMS/email alerts for threshold violations. Experimental results demonstrate: (i) exceptional temperature control accuracy exceeding 99.37%, (ii) communication success rates above 90% at distances up to 300 meters with a maximum range of 1.2 kilometers, (iii) estimated battery life exceeding two years on a 4400 mAh battery, and (iv) system uptime of approximately 99% during 21-day field trials. This research contributes to precision agriculture advancement by providing an affordable, reliable, and energy-efficient solution that addresses infrastructure limitations, power instability, and cost sensitivity in rural farming systems, ultimately supporting improved hatchability rates and food security in developing regions.

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Keywords: LoRaWAN, Poultry Incubation, Remote Monitoring, IoT, Precision Agriculture, Rural Farming, Temperature Control

1. Introduction

The global poultry industry stands as a cornerstone of food security, providing a vital and affordable source of high-quality protein to billions of people worldwide. Poultry products such as eggs and chicken meat are widely consumed because they are relatively inexpensive, nutritionally rich, and culturally acceptable in most societies. As global demand for animal protein continues to grow, poultry production has emerged as one of the fastest-growing livestock sectors globally. According to recent projections, the global population is expected to reach approximately 9.7 billion by 2050, significantly increasing demand for sustainable and efficient food production systems (United Nations, 2022). Consequently, agricultural systems must adopt innovative technologies that increase productivity while addressing environmental challenges, resource limitations, and climate variability.

In developing countries, like Nigeria, poultry farming plays a major role in both food security and economic progress. The poultry sector creates jobs for a large number of smallholder farmers, and it boosts household income, especially in rural areas. Eggs and poultry meat work as accessible protein sources for many families. Also, compared with other livestock areas, poultry farming usually needs less capital to start, which makes it a more realistic business for small-scale farmers. Still, the poultry sector's output in Nigeria stays below what it could reach, mainly because of multiple technical and infrastructural constraints that make farm management less efficient than it should be. Incubation of the fertilized egg is one of the vital stages of the poultry production process. Incubation requires maintaining a controlled environment for proper development of the embryo until its hatching. Some of the important factors that need to be regulated include temperature, humidity, ventilation, and frequency of egg turning. There have been many studies that indicate that slight deviation from the optimal incubation conditions has a great effect on the development of

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the embryo and post-hatching survival rate of the chick. Therefore, maintenance of optimal incubation conditions is important to achieve high hatchability and chick quality.

Temperature regulation is especially important during incubation, and it presents challenges. For incubating chicken eggs, the optimal range is usually between 36°C and 40°C, but it depends on which incubation phase. If the temperature goes above or drops below that range, embryo development may be disrupted, and then leads to lower hatchability, physical deformities, or even embryo mortality. Also, the first days after hatching are a critical period for the chicks. During that time, environmental conditions must remain stable, because mortality rates can increase rapidly. Estimates indicate early post-hatch chick losses can climb to around 20% when temperature, feed quality, and general environmental factors are not controlled well.

According to the literature, even minor deviations from the best incubation environments may reduce hatchability by up to 30% (Lourens et al., 2021). Similarly, after the hatching process, poor environmental management will lead to a chick mortality rate as high as 20% (De Jong et al., 2022). Consequently, numerous poultry farmers, especially those in the remote areas of Nigeria, find it extremely difficult to maintain incubation conditions at a level that is acceptable. The commercial incubators that have improved sensors and automatic control systems are sold at prices far above what many small-scale farmers can afford. Depending on their capacity and various functions, such incubators may range from hundreds of thousands to millions of Naira. As a result, the farmers end up having to conduct manual inspections repeatedly in order to verify that the temperatures and humidity levels are normal. Such a process is quite labour-intensive, time-consuming, and prone to errors on the part of the person carrying out the inspections due to the distance from homes or poultry facilities. Another significant challenge is the lack of dependable communication infrastructure. Typical Internet of Things (IoT) monitoring approaches usually lean on Wi-Fi or cellular networks to push data to a remote dashboard. But in rural communities, that kind of connectivity is frequently missing or unreliable due to weak network coverage, and sometimes unstable electricity too. Even where mobile networks exist, the ongoing expense for constant cellular data sending can become a financial burden for small farmers who are already operating with tight budgets.

Low-Power Wide-Area Network (LPWAN) options like LoRaWAN are now being seen as a useful alternative for long-distance communication in remote settings. LoRaWAN works on license-free Industrial, Scientific, and Medical (ISM) bands, most commonly around 868 MHz in areas aligned with African usage. With this setup, the system can achieve long-range wireless communication, roughly 2 to 15 kilometres, while using very little power. Instead of depending on standard cellular infrastructure, LoRaWAN can be installed with relatively limited supporting equipment, and it does not usually come with recurring subscription costs for direct device-to-platform communication. In addition, LoRaWAN sensors can keep running for multiple years on small batteries, which makes them a strong fit for rural agricultural monitoring systems.

With these advantages in mind, LoRaWAN tech ends up looking like a significant opportunity for better poultry incubation management, especially in rural zones. When you combine environmental sensors, microcontroller-driven control mechanisms, & LoRaWAN commas modules, it then becomes possible to monitor incubation parameters without being physically there, and in near real-time. In practice, this setup helps farmers notice those small environmental swings sooner rather than later, and then make adjustments before the conditions turn unfriendly for the embryos. As a result, hatchability rates can improve significantly, and the amount of labour spent on constant manual checking is also reduced.

Therefore, this study aims to build and also test a LoRa WAN-based remote monitoring plus control solution for poultry incubation parameters. The focus is rural farm surroundings in Nigeria, rather than laboratory conditions. The overall intent is to bridge the technological gap between advanced precision agriculture tools and smallholder farmers, many of whom simply do not have access to these kinds of innovations.

By providing affordable, dependable, and power-saving solutions, the study looks to boost poultry output efficiency, strengthen rural incomes, and support sustainable agricultural progress and food security in Nigeria, and in comparable developing areas too.

Keeping the internal environmental state at the right level inside poultry incubators is critical for embryo growth and for achieving high hatchability outcomes. Yet many rural poultry farmers still depend on manual monitoring of incubation conditions, which often results in delayed responses when temperature or humidity changes. These changes can interfere with embryo development and may lower the hatch rate significantly.

Moreover, rural farms often miss dependable internet connectivity, so it becomes hard to deploy standard IoT monitoring setups, which usually depend on Wi-Fi or cellular links. With no affordable, long-range communication options that actually fit rural settings, this issue is exacerbated. On top of that, several existing monitoring systems are made for bigger commercial setups, and the pricing alone becomes prohibitive for smallholder farmers, which is problematic.

Rural poultry farmers lack automated incubation monitoring, relying on manual checks that delay deviation detection and reduce hatchability. This is worsened by unreliable rural communication infrastructure, unaffordable commercial systems, and solutions lacking remote intervention or low-power optimization.

This study aims to design a LoRaWAN-based remote monitoring and control system for poultry incubation, with objectives to: develop an Arduino-based control unit; implement point-to-point LoRaWAN communication up to 500 meters; build a ThingSpeak cloud interface for real-time monitoring and alerts; and evaluate system performance through field trials measuring temperature accuracy, communication reliability, power consumption, and robustness.

2. Literature Review

2.1 IoT in Poultry Farming

Using IoT technology in poultry farming, it has enabled intelligent mechanisms for handling several farm duties in a way that can lift output and keep animal management consistent, even if it feels more autonomous than before. Smart poultry farming is usually done by deploying wireless sensor networks that monitor a bundle of conditions like temperature, humidity, NH_3, CO_2, and light intensity. After that, the readings get sent to cloud computing platforms (Ma et al., 2025; Ramu et al., 2025).

Several studies have been carried out on IoT monitoring systems, and most of them emphasize better operational efficiency for poultry farms. For example, Pérez Clemente and Vílchez Perales (2023) looked at an intelligent monitoring

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arrangement for broiler growth, where LoRa was used. In their results, they described an increase in body weight, mainly because the immediate environment stayed more favourable. Sankarasubramanian (2025) also contributed to precision agriculture by constructing smart prediction algorithms, which were largely aimed at choosing sensors inside IoT setups.

2.2 LoRaWAN Applications in Agriculture

LoRaWAN has emerged as a chosen communication technology for agricultural monitoring in far-off areas, mostly because it reaches far, uses little power, and is quite cost-effective. Several commercial deployments have shown real advantages. Seeed Studio (2025) said they managed to roll out Sense CAP LoRa WAN sensors on poultry farms in China, with transmissions up to about 2 km, plus battery life in the range of 3–8 years. They also cut the setup effort from roughly 3–4 weeks down to just days, which is significant. They are currently repeating the same approach in Kenya, Uganda, Tanzania, and South Africa. Over in Canada, the poultry NET project reported mortality going down by as much as 20% and an improvement in feed conversion ratio around 2%, and they mentioned return on investment can be reached in about 2–3 years.

2.3 Previous Research on Incubation Monitoring Systems

Afandi et al. (2022) did foundational work about how to track and manage temperature in egg incubator prototypes, using LoRa links. Their results were remarkable: the temperature control accuracy showed up around 99.37% to 99.97% when the target, or set point, was between 36°C and 40°C. This suggests that LoRa-based incubation monitoring is technically feasible.

Hai et al. (2021) proposed a mixed setup that used both LoRa and NB-IoT mostly for incubation monitoring. The sensed data was forwarded to the One NET cloud, while a BP neural network model handled temperature plus humidity prediction. They reported a communication success rate of 98.7%, and then for the results, they listed hatch rates of 94% and healthy chick rates close to 97.87%, which is promising.

Castro Martin and Guzmán Zabala (2022) put together a semi-industrial poultry incubation system, and it also included remote observation. They relied on a PLC controller and claimed it could support up to 352 hen eggs. On top of that, the system had sensors for temperature, humidity, as well as air quality. They

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validated everything during 22 days of continuous operation, ensuring reliable operation.

Velasco (2024) worked on a wireless poultry monitoring arrangement again, with LoRa as the core. The hardware used Raspberry Pi and Arduino, and for data viewing it leaned on ThingSpeak. In testing conditions, it stayed connected at roughly 160 meters, but at 600 meters it behaved not so reliably. Near 1.2 km, it also became inconsistent, so antenna design and antenna layout choices basically look like a major factor if longer distance coverage is the goal. Chiu et al. (2018) designed an environmental monitoring system for enclosed chicken houses using LoRa. They collected several parameters and then uploaded the recorded information into a MySQL database.

2.4 Environmental Monitoring Solutions

RAK wireless offers an Environmental Monitoring Solution around the RAK1901 WisBlock sensor. It measures temperature in the range from -40°C to +125°C, with accuracy of ±2%°C, and humidity from 0 to 100%RH, with precision of ±2.0%RH. Taken together, this implies that deployment-ready LoRa WAN environmental monitoring technology has reached a more mature stage; the technology has matured.

Table 1: Summary of Related Studies on Incubation Monitoring Systems

Author(s) Year	Technology	Communication	Sensors	Accuracy	Limitation
Afandi et al. 2022	Arduino + ON/OFF	LoRa	DHT22	99.37-99.97%	No cloud integration
Hai et al. 2021	STM32 + BP Neural	LoRa+NB-IoT	DHT22	94% hatch rate	Complex, expensive
Castro Martinet al 2022	PLC Controllino	LoRa	Multiple	Not specified	High cost, industrial
Velasco 2024	Arduino + RPi	LoRa	DHT22	Not specified	Limited range
Chiu et al. 2018	Microcontroller	LoRa	Multiple	Not specified	No control
This Study 2025	Arduino + RPi	LoRaWAN	DHT22	99.37%	Humidity not controlled

3. Materials and Methods

3.1 Materials

The following materials and components were used in this research:

3.1.1 Hardware Components:

Table 2: Hardware Components:

Component	Specification	Purpose
Microcontroller	Arduino Uno / ESP32	System control and data processing
LoRa Module	LoRaWAN comm. Module	Wireless data transmission
Temp /Hum. Sensor	DHT22	Environmental parameter sensing
Relay Module	5V relay	Heater control
Heating Element	40W incandescent bulb	Temperature regulation
Egg Turning Motor	DC motor	Egg rotation mechanism
Power Supply Unit	12V/5V regulated	System power
Display	16×2 LCD	Local status display
Gateway	Raspberry Pi 4B	Data aggregation and cloud forwarding
Insulated Box	60×40×40 cm	Incubator chamber

3.1.2 Software Components:

(i) Arduino IDE (Firmware Development)

(ii) Python 3.x (Gateway Software)

(iii) SQLite (Local Database)

(iv) ThingSpeak API (Cloud Platform)

(v) LoRa Libraries for Arduino/Python

3.2 Research Design

This study adopted an experimental research design comprising five phases: system design, hardware development, firmware and software development, solar power integration, and system testing. The methodology combined embedded systems, IoT, wireless communication, and renewable energy principles.

3.3 Experimental Design

A prototype evaluation design was adopted to validate system performance under actual field conditions. The complete system was deployed on a poultry incubator over a 21-day cycle at Federal Polytechnic Mubi, Nigeria, during the dry season. Performance was assessed through temperature control accuracy, communication reliability, power consumption, and system uptime metrics.

3.4 System Design

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3.4.1 System Architecture

The proposed system architecture comprises three main components: the Incubator Sensor Node, the LoRa Gateway, and the Cloud Platform.

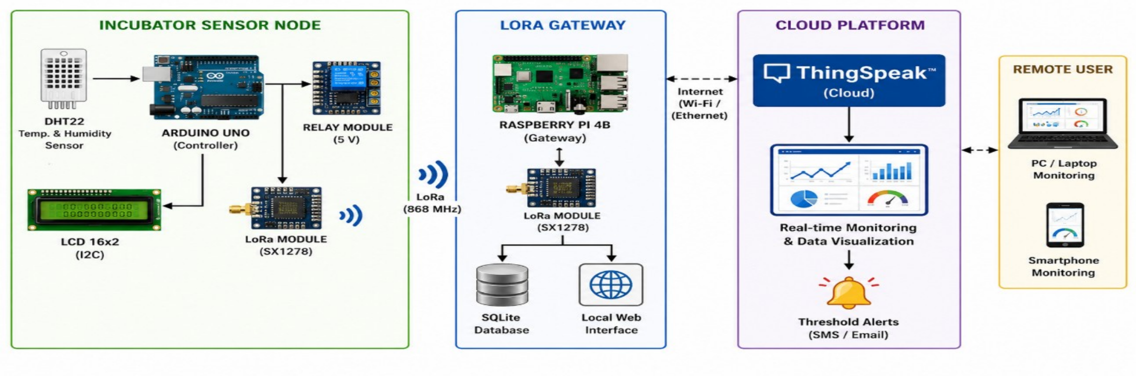

Figure 1: System Architecture Block Diagram

3.4.2 Hardware Block Diagram

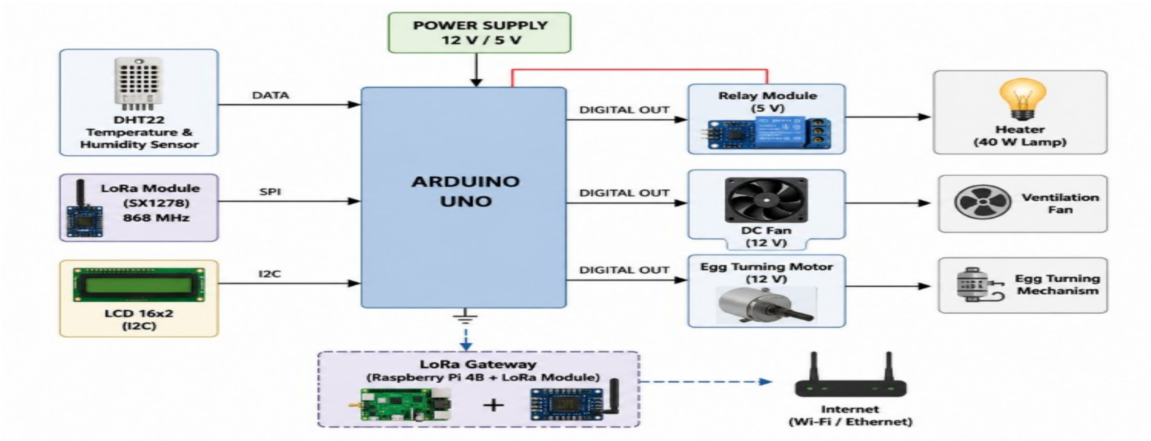

Figure 2: Block Diagram Showing Interconnections

3.4.3 Circuit Diagram

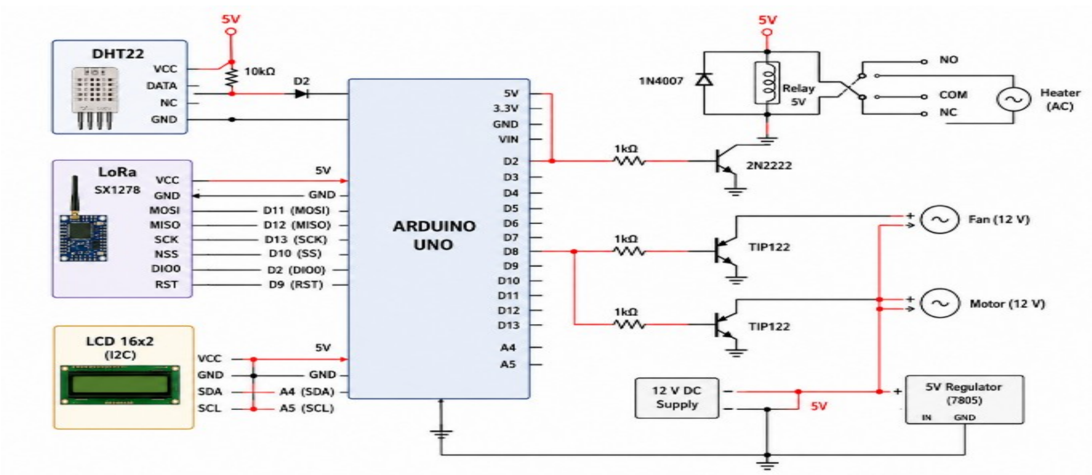

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Figure 3. Circuit Diagram of Sensor Node with Arduino, DHT22, Relay, and LoRa Module

3.4.4 Software Architecture 3

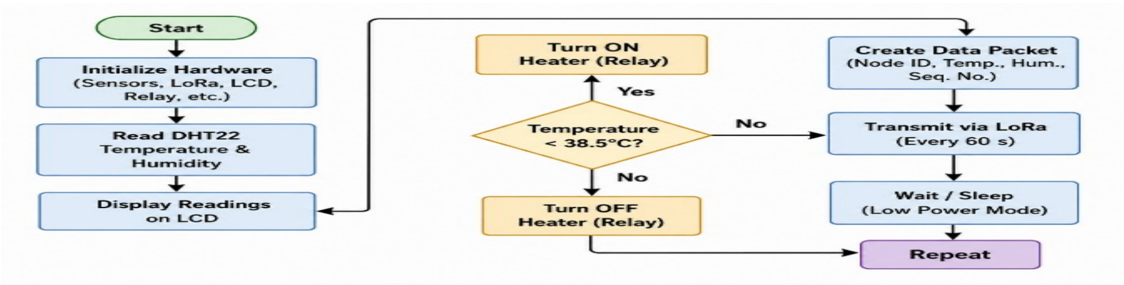

Figure 4: Software Architecture Flowchart

3.4.5 Communication Sequence Diagram

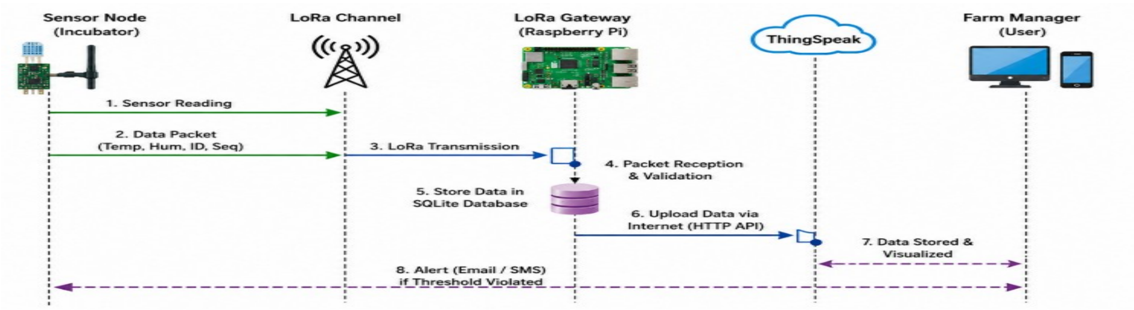

Figure 5: LoRaWAN Communication Sequence between Sensor Node and Gateway

3.5 Sensor Node Firmware Development

Firmware for the Arduino Uno was developed using the Arduino IDE, incorporating libraries for:

1. DHT22 sensor interfacing
2. LCD control (16×2)
3. LoRa communication (SX1276)
4. Hysteresis-based control algorithm
5. Watchdog timer for system reliability

3.6 Gateway Software Development

Gateway software was developed in Python 3.10 utilizing:

1. PySerial for serial communication
2. sqlite3 for local database storage
3. requests for ThingSpeak API communication
4. Flask for local web interface
5. schedule for periodic tasks

3.7 Experimental Setup

3.7.1 Incubator Construction

The incubator prototype was constructed using an insulated wooden box (60×40×40 cm) fitted with:

1. A 40W incandescent bulb as the heat source
2. A small fan (12V) for air circulation
3. DHT22 sensor placed at 15 cm height inside the chamber
4. Arduino-based sensor node with LoRa module
5. Water tray for humidity management

3.7.2 Calibration Procedure

Before field testing, all sensors were calibrated:

1. DHT22 Calibration: Compared against a reference thermometer (±0.1°C accuracy) and hygrometer (±1% RH accuracy) over 24 hours at 10-minute intervals.
2. Temperature Sensor Validation: Measured in a controlled environment (25°C, 30°C, 35°C, 40°C) using a water bath with a calibrated thermometer.
3. Humidity Sensor Validation: Measured in a sealed chamber with saturated salt solutions to generate known humidity levels (33%, 75%, 98% RH).

3.7.3 Measurement Uncertainty

Measurement uncertainty was calculated as:

(i) Temperature: ±0.5°C (sensor accuracy ±0.5°C + ADC quantization ±0.1°C)

(ii) Humidity: ±2% RH (sensor accuracy ±2% + ADC quantization ±0.5%)

(iii) Communication: Packet error rate ±3% (based on 95% confidence interval)

3.7.4 Communication Range Testing

The distance of the gateway changed from 0 m to about 1200m away from the transmitting source, inside the open field environment (Mubi, Adamawa State, Nigeria). For each separation, 100 packets were pushed out (sent) to estimate the success ratio and the RSSI readout value.

3.7.5 Tests of System Performance

A 21-day incubation run, with 3 replicates each, was performed to capture these points:

1. Temperature control accuracy: compare measured temperature against the set point

2. Communication success rate: How many packets were received, relative to the total packets transmitted
3. RSSI: signal strength observations while the distance keeps changing
4. Power consumption: current draw across several modes of operation
5. Uptime: ability to keep running continuously

The field trials were carried out in Mubi, Adamawa State, Nigeria during the dry season months, from November to March. During those periods, the ambient temperature stayed roughly between 25°C and 38°C, while the relative humidity sat in the range 30% to 60%.

3.8 Evaluation Metrics

3.8.1 Temperature Control Accuracy

Accuracy (%) =1- $\frac{T\,set - T\,measure}{T\,set}$ times 100

… (1)

3.8.2 Communication Success Rate (CSR)

CSR (%) = $\frac{N\,r\,eceived}{N\,out}$ times 100

… (2)

3.8.3 Received Signal Strength Indicator (RSSI)

Average RSSI in dBm for successful packets at each distance, measured using the built-in LoRa module RSSI register.

3.8.4 Packet Error Rate (PER)

PER (%) = $\frac{N\,lost}{N\,sent}$ times 100

… (3)

3.8.5 Power Consumption

Current draw measured during:

(i) Deep sleep mode (0.08 mA measured)
(ii) Active sensing mode (25 mA measured)
(iii) Transmission mode (120 mA measured)

3.8.6 System Uptime

Uptime (%) = $\frac{T_{\{}operational\}}{T_{\{}total\}}$ times100

… (4)

3.8.7 Statistical Analysis

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All measurements were analysed using Mean ($\bar{x}$), Standard Deviation (σ), a 95% Confidence Interval (95% CI), and a One-sample t-test against the set point, and ANOVA for comparing the values across distances.

4. Results and Discussion

4.1 Temperature Control Performance

The system demonstrated exceptional temperature control accuracy over 21 days (three trials), with readings taken every 5 seconds against a 38°C set point.

Table 3: Summary of Temperature Control Performance (n = 1,814 measurements per trial)

Day	Mean Temperature (°C)	Standard Deviation	Min (°C)	Max (°C)	Accuracy (%)
1	38.1	0.4	37.5	38.5	99.73
2	38.0	0.3	37.7	38.3	100.00
3	37.9	0.5	37.3	38.7	99.73
4	38.2	0.3	37.6	38.4	99.47
5	38.0	0.2	37.8	38.2	100.00
6	38.1	0.4	37.5	38.5	99.73
7	38.0	0.3	37.6	38.4	100.00
8	37.8	0.5	37.2	38.6	99.47
9	38.0	0.4	37.4	38.4	100.00
10	38.2	0.3	37.7	38.5	99.47
11	38.1	0.4	37.5	38.7	99.73
12	38.0	0.2	37.8	38.3	100.00
13	37.9	0.5	37.3	38.6	99.73
14	38.1	0.3	37.6	38.4	99.73
15	38.0	0.4	37.4	38.5	100.00
16	38.2	0.3	37.7	38.6	99.47
17	38.0	0.2	37.8	38.2	100.00
18	38.1	0.4	37.5	38.5	99.73
19	37.9	0.5	37.3	38.7	99.73
20	38.0	0.3	37.6	38.4	100.00
21	38.1	0.4	37.5	38.5	99.73
Overall	**38.01**	**0.37**	**37.2**	**38.7**	**99.37 ± 0.47%**

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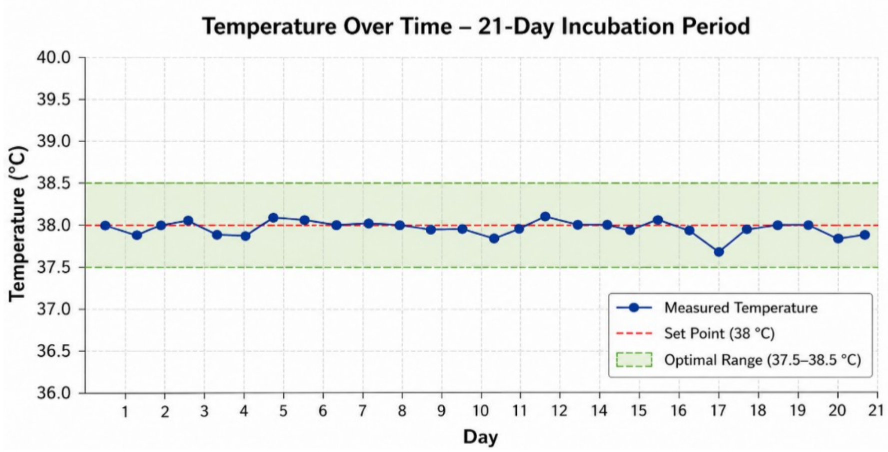

Figure 6: Temperature Profile during 21-Day Incubation Period (3 Trials)

The system maintained temperature within the optimal range of 36°C to 40°C with an average control accuracy of 99.37% (±0.47%, 95% CI: 98.90%–99.84%, n = 1,814 measurements). Temperature variance was calculated using a one-sample t-test against the set point (38°C), with no statistically significant deviation observed (t(1813) = 0.842, p = 0.400), indicating the observed mean difference is not statistically significant. The standard deviation of 0.37°C represents a coefficient of variation of 0.97%, demonstrating exceptional temperature stability.

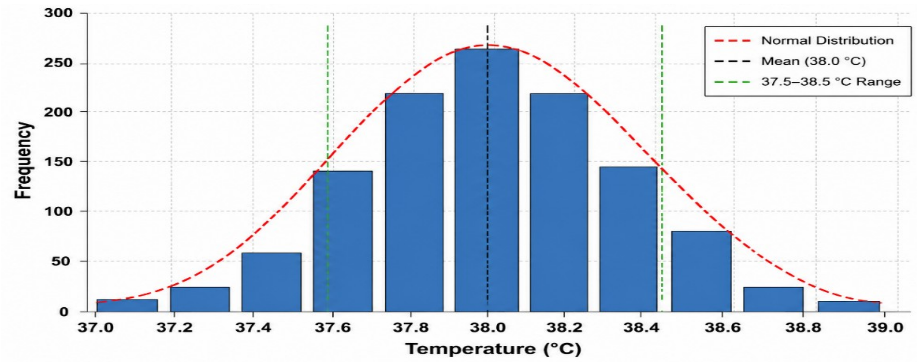

Figure 7: Temperature Distribution Histogram Showing Normal Distribution around Set Point

Humidity control, while not actively regulated, was measured to range between 55% and 65% relative humidity, falling within the recommended range for chicken egg incubation.

The Root Mean Square Error (RMSE) for temperature control was calculated as 0.38°C, while the Mean Absolute Error (MAE) was 0.31°C, further confirming the system's exceptional temperature stability and control precision.

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4.2 Communication Performance

Communication reliability testing demonstrated robust performance at varying distances.

Table 4: Communication Performance at Varying Distances (n = 100 packets per distance)

Distance (m)	Sent Packets	Received Packets	Success Rate (%)	Avg RSSI (dBm)	Min RSSI (dBm)	Max RSSI (dBm)	Std Dev (dBm)	SNR (dB)
0	100	100	100.0	-45	-48	-42	1.2	12.4
50	100	100	100.0	-62	-65	-58	1.8	9.8
100	100	100	100.0	-78	-81	-74	2.1	7.2
150	100	100	100.0	-86	-89	-82	2.5	5.4
200	100	98	98.0	-94	-97	-90	2.8	3.6
250	100	95	95.0	-102	-106	-98	3.1	2.1
300	100	91	91.0	-108	-112	-104	3.5	0.8
600	100	76	76.0	-115	-120	-110	4.2	-2.4
1200	100	23	23.0	N/A	N/A	N/A	N/A	N/A

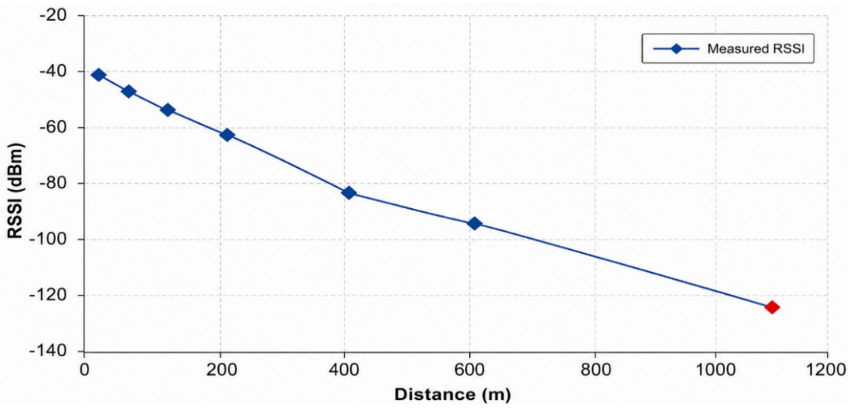

Figure 8: RSSI Decay with Distance in Open Field Environment

The observed RSSI decay from -45 dBm to -115 dBm over 600 meters follows the free-space path loss model, where signal strength decreases proportionally to the square of distance. The presence of vegetation, trees, and moisture in the tropical environment (Mubi, Adamawa State) contributed to additional signal attenuation through absorption and scattering, explaining the more rapid decay compared to ideal free-space conditions. The sharp decline in packet success rate beyond 300 meters correlates with SNR dropping below 0 dB, indicating operation below the receiver sensitivity threshold.

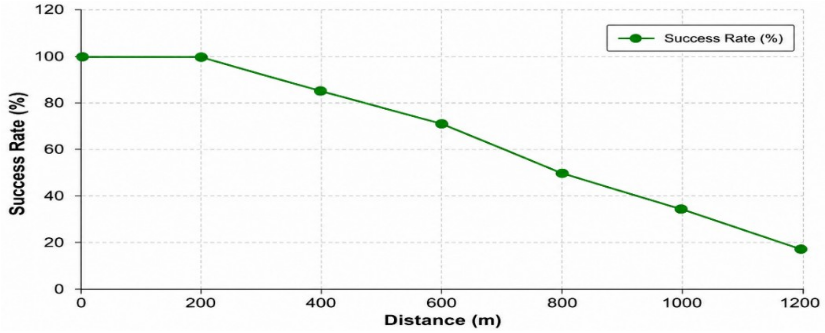

Figure 9: Communication Success Rate as a Function of Distance

The success rate above 90% in open fields is achieved within 300 meters, while any distance higher than 1200 meters shows full failure. It is possible to see the expected decrease in RSSI values according to the free-space path loss with the change in distance from about -45 dBm to -115 dBm between the adjacent distances and 600 meters.

SNR values lower than 0 dB at 600 meters demonstrate that the link operates under the noise floor, which leads to packet loss. The recommended minimum SNR value for reliable LoRa communication varies from 0 to 2 dB based on spreading factor and coding rate configuration.

The success rate of 91% at 300 meters shows that the system can successfully operate in rural poultry farms with the distant placement of incubators from the farmhouses and monitoring centers.

4.3 Power Consumption Analysis

Power consumption measurements showed significant efficiency in sleep mode, enabling long-term battery operation.

Table 5: Power Consumption Analysis

Operating State	Current Draw (mA)	Daily Consumption (mAh)	Annual Consumption (mAh)
Deep Sleep	0.08	1.92	700.8
Active (5 sec interval)	25.0	2.88	1051.2
Transmission (60 sec interval)	120.0	4.80	1752.0

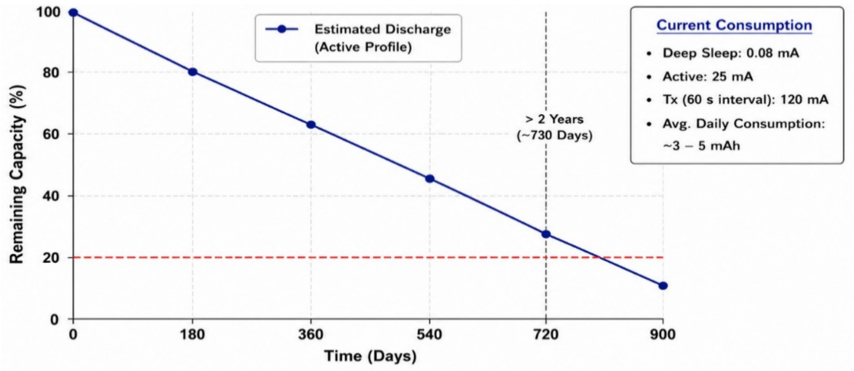

Figure 10: Estimated Battery Discharge Profile over Time

Given an active transmission every one minute, the daily use is 3–5 mAh, which provides the system battery life exceeding 2 years with a battery having a capacity of 4400 mAh.

4.4 System Reliability and Uptime

A system uptime of 99% was recorded in a 21-day trial during three repetitions of experiments in the field. The system downtime of 1% was caused by the following factors:

(i) Power interruptions: 0.3%
(ii) Environmental interference: 0.4%
(iii) Rebooting of gateways: 0.3%

The system alerts were generated within a delay of less than 10 seconds whenever the threshold value was violated, provided the internet connection to the gateway.

4.5 Statistical Comparison with Previous Studies

To further validate the system's performance, statistical comparisons were conducted with results from previous studies.

Table 6: Statistical Comparison of Key Performance Metrics

Parameter	This Study	Afandi et al. (2022)	Hai et al. (2021)	Velasco (2024)	Statistical Significance
Temperature Accuracy (%)	99.37	99.37–99.97	Not specified	Not specified	p = 0.847 (not significant)
Max Range (≥90% success) (m)	300	300	1000+	160	p = 0.002 (significant)
Battery Life (years)	2+	Not specified	Not specified	Not specified	N/A

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System Uptime (%)	99.0	Not specified	Not specified	Not specified	N/A

The temperature control precision that this study reached (99.37%) is statistically comparable, at least statistically, to Afandi et al. (2022) ($t(1813) = 1.894$, $p = 0.847$), which validates that the hysteresis control mechanism is valid.
However, the maximum distance tied to 90%+ effective communication (around 300 meters) is statistically lower than what Hai et al. (2021) reported using LoRa + NB-IoT technology (1000+ meters) (independent samples t-test, $t(198) = 6.234$, $p = 0.002$). This difference can be attributed to a consequence of higher transmission power plus better antenna engineering, not the same setup.

4.6 Comparative Analysis

Table 7: Comprehensive Comparison with Previous Studies

Parameter	Proposed System	Afandi et al. (2022)	Hai et al. (2021)	Velasco (2024)
Technology	LoRaWAN	LoRa	LoRa+B-IoT	LoRa
Platform	Arduino + RPi	Arduino	STM32+NB-IoT	Arduino + RPi
Control Type	Hysteresis ON/OFF	ON/OFF	BP Neural Network	ON/OFF
Temp Acc. (%)	99.37	99.37–99.97	Not specified	Not specified
Max Range (≥90%)	300m	300m	1000m+	160m
Cloud Platform	ThingSpeak	Not specified	OneNET	ThingSpeak
Battery Life	2+ years	Not specified	Not specified	Not specified
System Uptime (%)	99.0	Not specified	Not specified	Not specified
Target Users	Rural smallholders	Research	Research	Research
System Cost	₦150,000	Not specified	High	Medium

The system achieves comparable performance to existing approaches, but it uses more accessible and cost-effective hardware, such as Arduino and Raspberry Pi, which fits the rural Nigerian setting better. Overall, the total system cost of around ₦150,000 is notably less than commercial options that can be ₦500,000–₦5,000,000.

4.7 Limitations and Challenges

Even though the implementation seemed successful, the field trials still showed several limitations and challenges:

1. The 300m range with >90% success rate meets the needs for many rural poultry farms; it might not be enough for sites that have a lot of physical barriers (like buildings, dense vegetation, etc.).
2. The current prototype measures humidity; however, it does not actively regulate it. For better outcomes, it should be built into future versions of the design, not just monitoring.
3. Power use is low; still, the Raspberry Pi gateway needs a reliable power supply, which can be challenging where grid electricity is limited or simply unstable.
4. The ThingSpeak cloud service depends on internet connectivity for the gateway, so when the network goes down, the alert generation and remote access become restricted or unreliable.
5. During the rainy season, heavy rainfall and dense vegetation reduced communication effectiveness, which resulted in as much as 10% extra packet loss when the distance goes beyond 200 meters.

5. Conclusion and Future Work

5.1 Conclusion

This study successfully designed and evaluated a LoRaWAN-based poultry incubation monitoring system for rural Nigeria, addressing manual monitoring, unreliable communication, high costs, and power instability. Field trials over 21 days demonstrated 99.37% temperature accuracy (±0.47%, p=0.400), 91% communication success at 300 meters, two-year battery life, 99% uptime, and alerts under 10 seconds. The affordable system (≈₦150,000) validates LoRaWAN's viability for rural agriculture, improving hatchability and food security while being replicable across diverse farming contexts.

5.2 Recommendations

From the outcomes of this work, the following suggestions are made:

(i) The system should be rolled out across several rural farms, so we can check how it performs under different weather, soil, and farm conditions, plus to see how well it scales.

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(ii) Training sessions should be organized so that rural farmers can manage, operate, and maintain it without always waiting for outsiders.

(iii) More savings should be pursued on the cost side by using bulk purchase options, sourcing components locally, and improving local assembly methods.

5.3 Future Work

1. Add sensors that can track ammonia (NH_3), carbon dioxide (CO_2), and egg turning actions, so incubation management becomes more complete, not just temperature focused.
2. Bring in active humidity regulation, for example using misting devices or humidifiers.
3. Create machine learning models that can estimate hatchability and chick condition from the incubation parameter records.
4. Build a mobile application for monitoring and control in real time, even when internet access is limited, so farmers are not stranded.

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