IoT System for Monitoring the Physicochemical Quality of Irrigation Water: Towards Efficient Agricultural Management

Ilber Adonayt Ruge Ruge
Universidad Pedagógica y Tecnológica de Colombia
Department of Electronic Engineering
Tunja, Colombia
email: ilber.ruge@uptc.edu.co

Alvaro Torres Amaya
Universidad Pedagógica y Tecnológica de Colombia
Department of Technological Sciences
Tunja, Colombia
email: alvaro.torresa@uptc.edu.co

Maria José Clavijo Rodriguez
Universidad Pedagógica y Tecnológica de Colombia
Department of Electronic Engineering
Tunja, Colombia
email: maria.clavijo01@uptc.edu.co

Jorge Andres Palacios Torres
Universidad Pedagógica y Tecnológica de Colombia
Department of Electronic Engineering
Tunja, Colombia
email: jorge.palacios@uptc.edu.co

Abstract— **This paper describes the development and evaluation of an Internet of Things (IoT) system for monitoring physicochemical parameters in water, with potential applications in irrigation systems for crops, and was developed using low-cost sensors and an ESP32 microcontroller programmed with the Arduino® IDE. The system allows the real-time measurement of variables such as turbidity, Total Dissolved Solids (TDS), and water temperature. The acquired data is processed at the acquisition level and transmitted via Wi-Fi to the ThingSpeak cloud platform for storage and visualization, making it available for subsequent analysis and decision-making support. To evaluate accuracy, stability, and viability, experimental tests were carried out using standard solutions of different concentrations, comparing the measurements with laboratory equipment and theoretical values to ultimately develop a polynomial calibration model. The results show high performance of the TDS sensor, with relative errors of 6%-21% and a stable temperature measurement, with an error of about 4.7% compared to the reference instrument. In contrast, the turbidity sensor showed high variability, with errors ranging from 13% to 77% depending on the measured concentration. Furthermore, the influence of environmental factors on sensor response was demonstrated, highlighting the importance of calibration and control processes in water monitoring systems.**

Keywords- Internet of Things (IoT); Water quality monitoring; Arduino ESP32; Low-cost sensors; ThingSpeak.

I. INTRODUCTION

Water quality is a key factor in agricultural productivity as its physicochemical properties directly influence crop development and soil sustainability. Parameters such as turbidity, Total Dissolved Solids (TDS), and water temperature enable characterization of the water resource's condition and detection of factors that may affect irrigation systems. In this context, the periodic monitoring of these variables is essential to support more efficient water management, especially in environments where access to specialized instrumentation is limited [1].

The advancement of the Internet of Things (IoT) has driven the development of monitoring systems based on microcontrollers and low-cost sensors, capable of acquiring real-time data and transmitting it to cloud platforms for storage and remote visualization. These solutions facilitate access to relevant information on environmental variables and provide a technological foundation for subsequent analysis and informed decision-making. However, the reliability of these systems depends mainly on the accuracy of the sensors and the implementation of appropriate calibration and validation processes [2][3].

This paper presents the development and implementation of an IoT system for monitoring physicochemical water parameters, with potential applications in crop irrigation systems. The system is based on an ESP32 microcontroller programmed in the Arduino® IDE and integrates low-cost sensors for measuring turbidity, TDS, and temperature. The acquired data is transmitted via Wi-Fi to the ThingSpeak platform for cloud storage and visualization, making it available for subsequent analysis. This study focuses on the experimental evaluation of the system's performance and the sensors used, while considering the influence of environmental factors on the measurements. The paper is organized as follows: Section II presents related work, Section III describes the materials and methods, Section IV presents the results and discussion, and Section V presents the conclusions and future work.

II. RELATED WORKS

To ensure the rigor and transparency of the literature review process, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) methodology was adopted. This methodology defines a systematic procedure structured in four phases: identification, screening, eligibility, and final inclusion of relevant studies [4]. This approach enabled the objective organization and refinement of the literature on IoT systems and data acquisition.

The conducted search spanned widely recognized scientific databases and specialized repositories, including IEEE

Xplore, Scopus, ScienceDirect, MDPI, and Google Scholar, which focus on IoT systems for water quality monitoring. The considered works were published between 2019 and 2025 and describe experimental implementations of low-cost sensors, embedded platforms, and cloud-oriented data transmission. This review lets us identify technological trends, design approaches, and major limitations on IoT-based water monitoring systems.

TABLE I. RESULTS OF LITERATURE REVIEW.

Reference (Year) Title	Sensors / Hardware	Main result
Tavares de Camargo (2023) — *Low-Cost Water Quality Sensors for IoT: A Systematic Review [5]*	pH, TDS, turbidity, temperature.	Analyzes the performance and limitations of low-cost IoT sensors
Flores-Iwasaki (2025) — *IoT Sensors for Water Quality Monitoring in Aquaculture Systems [6]*	Physicochemical Sensors + IoT	Technological trends and applications in water monitoring
Rojas (2025) — *Sensors and IoT for Water Quality Monitoring [7]*	pH, TDS, turbidity, temperature.	Identifies gaps between laboratory and field
Jayaraman (2024) — *Critical review on water quality analysis using IoT [8]*	Various IoT Sensors	It points out challenges in calibration and reliability.
Lal (2024) — *Low-cost IoT based system for lake water quality monitoring [9]*	pH, TDS, turbidity	Functional, low-cost system validated in a lake
Bogdan (2023) — *Low-Cost IoT Water-Quality Monitoring System for Rural Areas [10]*	ESP8266, pH, TDS, turbidity	Viability in rural contexts; calibration dependence
Suriasni (2024) — *IoT Water Quality Monitoring in MBBR [11]*	Physicochemical Sensors + IoT	Stable monitoring in water treatment
Kanwal (2024) — *IoT-Driven Intelligent Decision-Making System [12]*	pH, temperature, turbidity	Advanced system with decision-making
Rosliana Eso (2024) — *IoT Water Quality Monitoring for Shrimp Farming [13]*	pH, TDS, temperature.	Improved control in aquaculture
Zafi (2024) — *Monitoring System Based on IoT and TDS Sensor [14]*	TDS, microcontroller	Validate the use of the TDS sensor in IoT
Jan (2025) — *IoT Based Water Quality Monitoring Using ESP32 [15]*	ESP32, basic sensors	Economic and replicable platform
Carriazo (2022) — IoT-Based Drinking Water Quality Measurement System (2022) [16]	—	Overview of IoT systems for drinking water
F. Jan (2021) — *IoT Based Smart Water Quality Monitoring [17]*	IoT sensors	Open challenges and future directions
Islam (2025) — Prediction Model of Aqua Fisheries Using IoT Devices (2025) [18]	ESP32, sensors, ThingSpeak	It integrates monitoring and prediction
Ayon (2026) — IoT-Enabled Smart Aquarium System (2026) [19]	ESP32, multiple sensors	Real-time monitoring in aquariums

The key approaches and contributions of the literature review are summarized and organized thematically, enabling analysis of trends in IoT systems applied to water quality monitoring.

Studies conducted by Tavares de Camargo, Flores-Iwasaki, Rojas, Jayaraman, Carriazo-Regino, and Jan on IoT-based water quality monitoring unveil the increasing use of low-cost sensors and communication platforms for the remote, real-time measurement of physicochemical parameters such as pH, temperature, turbidity, conductivity, and total dissolved solids. These systematic reviews and state-of-the-art analyses demonstrate the adoption of IoT architectures supported by low-power communication technologies and cloud platforms for data management and visualization, while also identifying persistent challenges related to interoperability, field validation, and the scalability of water monitoring systems [5]–[8][14][15].

The work presented by Flores-Iwasaki, Suriasni, Kanwal, Eso, Zafi, Islam, and Ayon demonstrates that, in aquaculture applications, IoT systems represent an effective solution for the continuous monitoring of critical conditions in fish farming, aquaponics, biofloc systems, and shrimp farming. These approaches integrate commercial sensors with microcontrollers such as Arduino and ESP32, enabling early detection of water-quality variations and, in some cases, implementing automatic control strategies to optimize system conditions. The reported experimental validation confirms their technical feasibility and their contribution to the sustainable management of aquaculture systems [6][11]–[14] [16]-[19].

Likewise, the work proposed by Lal, Bogdan, and Carriazo-Regino focuses on developing low-cost IoT systems for rural and natural environments, emphasizing accessibility, energy efficiency, and operational autonomy. These solutions facilitate continuous monitoring of water bodies in areas with limited infrastructure using widely available hardware platforms, thereby enabling environmental monitoring and timely access to relevant water-quality information [9][10] [14].

Finally, the studies conducted by Jayaraman, Kanwal, Jan, Islam, and Ayon show that integration of cloud-based IoT platforms with machine learning techniques significantly expands the capabilities of water monitoring systems. These approaches enable remote data visualization, alert generation, and intelligent water-quality classification with high accuracy, reinforcing the potential of IoT solutions as key tools for efficient and sustainable water resource management across diverse contexts [8][12][15]-[19].

III. METHODOLOGY

The development of the water physicochemical parameter monitoring system enabled a gradual evolution from basic data acquisition to the integration of IoT capabilities. Initially, the ATmega328P microcontroller was used to read and perform preliminary processing of the variables, thereby enabling validation of sensor functionality and system stability. Subsequently, an ESP32 development board was employed to enable Wi-Fi connectivity and automatically transmit data to the ThingSpeak platform, allowing for storage, management, and visualization in the cloud.

The system is designed to measure relevant physicochemical variables for assessing irrigation water quality, specifically temperature, TDS, and turbidity. These parameters allow for an initial characterization of the water resource's condition and its suitability for agricultural applications. Additionally, auxiliary modules were integrated to ensure proper data management, including a microSD card for local storage, a Real-Time Clock (RTC) for accurate date and time recording, and a Liquid Crystal Display (LCD) screen with an I2C interface, which facilitates immediate visualization of readings during field monitoring. The general scheme is illustrated in Figure 1.

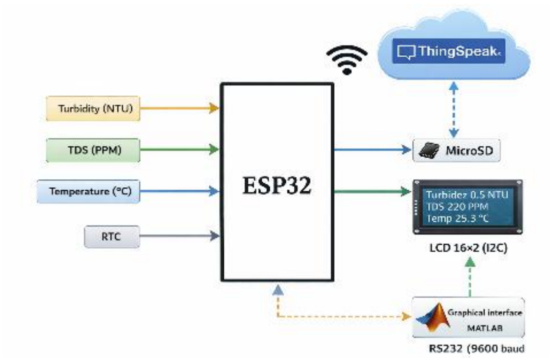

Figure 1. General scheme of the monitoring system.

The system's timing is defined using timer-based interrupt routines, ensuring the sequential execution of critical tasks, as shown in the flowchart in Figure 2. TMR0, configured with a 1-second interval, controls sensor sampling, LCD-based variable visualization, and data storage on the microSD card with RTC timestamps. Additionally, TMR1, configured with a 15-second interval, defines the interval for transmitting data to ThingSpeak via Wi-Fi and for visualization in MATLAB via RS232 at 9600 baud, enabling local monitoring without affecting the main algorithm.

The monitoring system incorporates turbidity, TDS, and temperature sensors, parameters widely used in the physicochemical evaluation of irrigation water quality. In this case, temperature is considered a critical variable because it directly influences dissolved solids measurements. Turbidity is measured using an analog optical sensor based on light transmission and scattering, capable of detecting suspended particles over a range of 0 to 1000 NTU. This sensor delivers an output signal between 0 and 4.5 V, allowing for continuous measurements with adequate resolution for environmental monitoring applications [20].

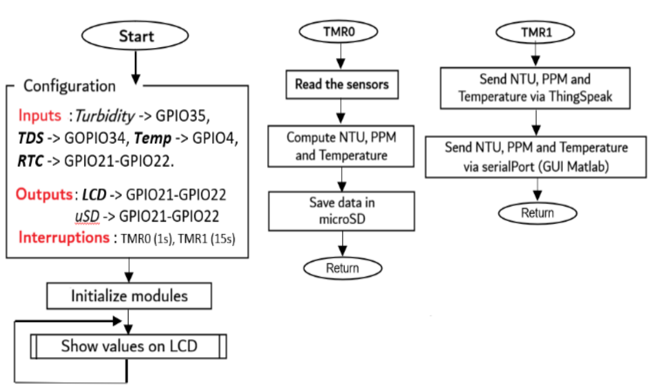

Figure 2. Flux diagram for the system.

TDS is measured using an electrical conductivity sensor with two electrodes. The analog signal from this sensor corresponds to the concentration of dissolved solids in the water and is converted to PPM units through an experimental calibration process. Since this sensor is sensitive to thermal variations, it requires temperature compensation to improve its accuracy [21]. For this purpose, the water temperature is recorded using a DS18B20 submersible digital sensor, designed for liquid applications. This sensor offers high stability, reliable digital communication, and a suitable measurement range, facilitating its integration with the microcontroller and the required thermal compensation [22]. The calibration of the turbidity and TDS sensors was performed by preparing standard solutions with known concentrations. This procedure was carried out in the Water Treatment Laboratory of the Department of Environmental Engineering at the Pedagogical and Technological University of Colombia, under specialized technical supervision. For turbidity, formazin, the primary standard recommended by APHA regulations, was used, starting from a 4000 NTU stock solution, from which solutions between 10 and 100 NTU were obtained by controlled volumetric dilution, applying the relationship shown in (1).

$$C_1V_1 = C_2V_2 \tag{1}$$

where C_1 and V_1 correspond to the concentration and volume of the stock solution, and C_2 and V_2 to the desired concentration and volume. The actual turbidity values of the standard solutions were determined using a Merck TurbiQuant® 1500 T benchtop turbidimeter, a reference instrument designed for precise and repeatable measurements in NTU units. Similarly, the TDS sensor was calibrated using a 10,000 PPM stock solution prepared with soluble salts in ionized water, obtaining concentrations between 200 and 2000 PPM by controlled volumetric dilution. The actual TDS values were measured using a Hanna Instruments HI 9811-5 multiparameter meter, which integrates pH, electrical conductivity, and TDS measurements with automatic temperature compensation, ensuring reliable readings. The turbidity and TDS sensors were characterized by measuring their output voltage against solutions of known concentration, recording three readings per point to reduce noise. Average values were used to plot voltage-concentration curves. The analysis revealed polynomial behavior in the sensor response, so regression was applied to obtain quadratic models implemented on the microcontroller, allowing real-time conversion of analog voltages to physical turbidity and TDS values. To evaluate the sensors' stability under ambient conditions, the influence of temperature on their response was analyzed, as shown in Figure 3. The results show a slight thermal drift, evidenced by a systematic shift in the calibration curves across different temperatures. This effect is greater in the TDS sensor because electrical conductivity depends on temperature, whereas in the turbidity sensor, the variation is less significant.

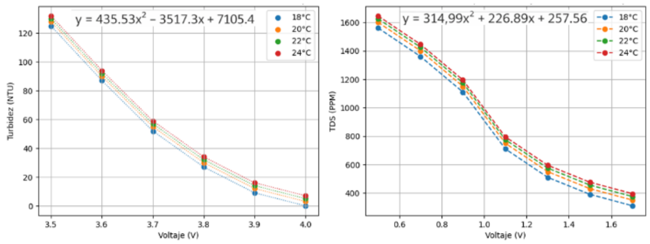

Figure 3. Characteristic equations of Turbidity and TDS.

IV. RESULTS AND DISCUSSION

The system performance was validated by comparing measurements from turbidity (NTU) and TDS sensors with values recorded by standard instruments and with the theoretical concentrations of the prepared solutions. The results are presented in Tables II and III.

TABLE II. COMPARISON OF TURBIDITY VALUES.

	Obtained data from turbidity sensor (NTU)						
Theoretical value	**Reference instrument measurement**	**Data 1**	**Data 2**	**Data 3**	**Data 4**	**Mean**	**Error**
10	11.6	11.68	16.5	16.7	16.8	16.72	44%
20	22.3	16.2	16.0	16.2	16.33	16.18	27%
30	36.1	31.29	31.1	31.2	31.45	31.37	13%
40	48.5	86.36	86.36	85.0	85.9	85.98	77%
50	56.6	88.52	88.7	88.21	87.0	88.26	56%

(*) Nephelometric turbidity unit
(**) Squared error with respect to the value of the reference instrument

TABLE III. COMPARISON OF TDS VALUES.

	Obtained data from TDS sensor (ppm)							
Theoretical value	**Reference instrument measurement**	**Data 1**	**Data 2**	**Data 3**	**Data 4**	**Mean**	**Mean deviation**	**Error**
400	509	631	536	586	558	571	42.7	12%
600	774	938	900	954	978	938.2	26.8	21%
800	1095	1211	1201	1220	1250	1216	18.7	11%
1000	1300	1377	1358	1360	1377	1372	11.4	6%
1200	1524	1424	1420	1430	1400	1417.2	10.4	7%

(*) Parts per million
(**) Error calculated with respect to the reference instrument

The results for turbidity, presented in Table II, show that the sensor's performance is strongly dependent on the measurement range. For low turbidity values (10 and 20 NTU), high error rates of 44% and 27%, respectively, were observed, indicating a notable tendency toward overestimation compared to the reference instrument. Although the standard deviations were low, indicating good repeatability, the systematic differences from the reference values suggest limitations in the sensor calibration within these ranges.

The best performance was observed at around 30 NTU. The results show that the error was reduced to 13% and that the average measured value approached that of the reference instrument, while maintaining low dispersion. This behavior indicates that this range corresponds to the optical sensor's optimal sensitivity point. In contrast, for concentrations above 40 and 50 NTU, a significant loss of linearity was observed, with errors of 77% and 56%, respectively. In these cases, the sensor recorded values much higher than the actual values, suggesting saturation of the optical system, a common phenomenon in transmissivity-based sensors.

Overall, the turbidity sensor produces an average error of 44%, limiting its reliability, especially outside the 20-30 NTU range. These results suggest either restricting its operation to intervals where it shows greater stability or implementing more robust calibration models that compensate for nonlinear effects and saturation phenomena observed at higher concentrations.

The TDS sensor exhibited more stable and consistent performance, as shown in Table III. At low concentrations of 400 and 600 PPM, a systematic overestimation was observed, with errors of 12% and 21%, respectively, attributable to the sensor's sensitivity at low conductivities and the thermal influence of the measurement method. From 800 PPM upwards, performance improved significantly, with the error decreasing to 11% and the standard deviation decreasing. The best performance was observed in the 1000 and 1200 PPM ranges, with errors of 6%-7%, high stability, and good reproducibility. The overall system error was 11%, demonstrating greater accuracy and reliability of the TDS sensor compared to the turbidity sensor. These results show that error tolerance depends on the application context. In agricultural irrigation, larger margins can be accepted without significantly affecting decision-making, while urban applications or wastewater management require stricter levels of accuracy and stability. Consequently, it is necessary to define specific performance metrics for each implementation scenario.

The system demonstrates stable performance in the remote transmission and visualization of turbidity, TDS, and temperature data via the ThingSpeak IoT platform. As shown in Figure 4, the measurement system works along with the communication infrastructure and graphical interface, assigning each variable to an independent field within the configured channel. The data are stored and graphically represented over time, enabling temporal monitoring of the measured physicochemical parameters.

Data transmission was performed at 15-second intervals, ensuring reliable communication in accordance with ThingSpeak's restrictions. This interval prevents congestion, optimizes energy consumption, and provides adequate resolution for continuous monitoring, validating the system's viability for remote supervision. However, Wi-Fi connectivity can be limited in rural environments with restricted coverage. In this context, LPWAN (Low-Power Wide-Area Network) technologies, designed for long-range, low-power communication, emerge as a viable alternative. In particular, LoRa (Long Range) enables the implementation of distributed monitoring networks with greater coverage and energy efficiency.

The graphical user interface (GUI) enabled real-time local monitoring of turbidity, TDS, and temperature, as well as data logging and exporting for later analysis. This graphic environment was developed in MATLAB using App Designer and provides an interactive application with control buttons, tables, graphs, and display panels, as shown in Figure 4. The GUI included menus for each measured variable, allowing dynamic switching between signals from the microcontroller. It also included options to start and stop data acquisition, generate Excel files, and implement a basic authentication mechanism. Overall, the interface proved to be a functional

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tool for local monitoring, data management, and system control, complementing remote cloud-based visualization.

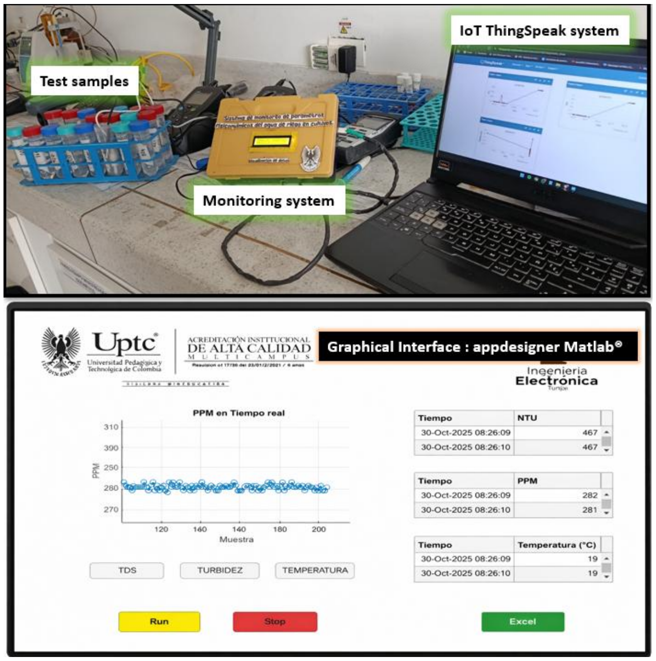

Figure 4. Characteristic equations of Turbidity and TDS

From an economic perspective, the developed IoT system significantly reduces costs compared to commercial instruments. As stated in Table IV, the final cost is about USD 59, much lower than commercial equipment, such as portable turbidimeters or professional TDS meters, which range from USD 150 to over USD 3,900 (Table IV). As for functionality, our prototype features turbidity, TDS, and temperature measurements, local storage, graphical interface visualization, and remote cloud monitoring. In comparison, commercial equipment generally does not offer integrated monitoring or native data transmission. Furthermore, some commercial devices require additional software licenses for graphical interfaces or data management. This difference positions our IoT system as a viable alternative for educational settings, rural applications, and continuous monitoring with limited budgets. Although commercial equipment offers greater certification and accuracy, our prototype meets the functional requirements for measurement, visualization, and transmission; under these conditions, our device becomes an accessible, integrated option for water quality monitoring.

The presence of thermal drift and the variability observed in the turbidity sensor highlight the need to implement specific calibration processes and compensation mechanisms to improve measurement accuracy. Despite these limitations, the system exhibits stable data acquisition and transmission, validating its viability as a low-cost monitoring solution for agricultural applications and resource-constrained environments. Furthermore, its architecture, based on low-cost sensors and IoT connectivity, enables adaptation to urban scenarios, such as monitoring in storage tanks or drainage networks. However, these applications require higher precision and reliability, necessitating calibration process adjustments tailored to the specific usage context.

TABLE IV. COMPARISON OF COSTS.

Developed IoT system	Associated Variable	Cost (USD)
Turbidity sensor	Turbidity	14.5
TDS Sensor	TDS	15.2
Temperature Sensor	Temperature	2.9
LCD + I2C module	Visualization	6.5
SD module	Data recording	1.3
RTC module	Time	2.1
Power source	Energy	1.8
ESP32	Processing / IoT	9.2
Structure and wire	Hardware assembly	6.6
IoT system subtotal	Turbidity, TDS, Temperature	**59**
Commercial solutions		
Professional Portable Turbidimeter	Turbidity **(Hanna Instruments)**	**315 – 920**
TDS meter / Professional Conductivity	TDS **(Extech Instruments)**	**158 – 395**
Commercial multiparameter system	Multiple variable **(Hanna Instruments)**	**1580 – 3950**

V. CONCLUSIONS

The monitoring system has demonstrated the feasibility of integrating low and mid-cost sensors, IoT platforms, and experimental calibration to measure turbidity, TDS, and temperature in real time. The prototype, based on an ESP32 microcontroller, includes data storage, local visualization, and transmission to the cloud via ThingSpeak, recording continuous and structured information. The preparation of standard solutions and the construction of polynomial calibration models enabled a quantitative evaluation of the sensors' performance; the results reveal their metrological capabilities and limitations.

The results show that the system's performance depends on the concentration range, sensor characteristics, and the physical conditions of the medium. The TDS sensor exhibited an overall error of 11%, with greater stability in the mid- and high-range measurements. In comparison, the turbidity sensor reached an error of 44%, with overestimations in the low and high ranges. On the other hand, the temperature measurement, with an error of approximately 4.76%, allowed for the required thermal compensation. Data transmission via Wi-Fi and the ThingSpeak platform enables remote monitoring of the variables, though it can be limited in rural environments with restricted connectivity. In general, the system is a functional, scalable, and low-cost solution; however, its long-term viability depends on optimizing energy consumption and implementing appropriate maintenance strategies to ensure its continuous operation.

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