An Embedded IoT-Based System for Real-Time NPK Soil Quality Monitoring in Precision Agriculture

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ABSTRACT

This study presents a soil quality evaluation framework that incorporates a JXCT NPK sensor, a pH electrode, a temperature detector, and an Arduino unit capable of real-time monitoring of nutrients. Traditional soil testing techniques are still slow, labor-intensive, and not available to most rural farming communities. The proposed system overcomes these drawbacks by integrating multi-parameter sensing and local and remote visualization using an LCD and an Android application. Mathematical modeling of the electrochemical and optical principles of sensing, linear calibration functions, and equations of nutrient balancing support the hardware. Five types of common soil were experimented on, including sandy, clay, loamy, peaty, and silty soils. Nitrogen (N), Phosphorus (P), Potassium (K), pH, and temperatures were compared to agricultural reference standards, and absolute percentage errors were calculated. The findings indicate high accuracy for nitrogen and phosphorus (0–15% and 10–33% error ranges). However, K measurements exhibited significant deviation (>50%) due to ionic cross-sensitivity. Consequently, the system is recommended for quantitative analysis of nitrogen and phosphorus, but strictly for qualitative trend monitoring regarding potassium levels. The two-screen system (LCD and Android app) was proven to have a stable real-time performance. The results support the promise of embedded sensing systems based on low-cost devices to facilitate precision agriculture and enhance decision-making on fertilizers, especially in areas with scarce resources.

Keywords-soil quality monitoring; embedded systems; precision agriculture; electrochemical sensing; real-time data acquisition

I. INTRODUCTION

Farming is fundamental to food security, especially in developing countries. Soil fertility determines the yield of the crop. The physicochemical health of the soil is dependent on macronutrients, including nitrogen (N), phosphorus (P), and potassium (K), whose time-of-the-year apportionment is of utmost value in optimizing fertilizer use. Although traditional laboratory methods have been the norm [1], they are usually constrained by their expensive nature, the slow process duration, and the requirement for special equipment. In an attempt to solve these dilemmas, quick testing models have been used to determine soil health in various settings [2]. The management of nutrients is critical to avoid long-term soil degradation in smallholder farms [3]. Current developments in the fields of embedded systems and IoT have opened cost-effective opportunities in real-time soil quality measurements [4]. Arduino and NodeMCU are examples of low-power microcontrollers that are used to connect electrochemical NPK, pH, and temperature sensors to wireless modules. These platforms allow autonomous in situ measurement of vital soil parameters, which can be used to achieve data-driven precision agriculture with a minimum of human input. In [5], the synergy of smart sensing with data analytics to optimize agricultural inputs was reviewed, while in [6], a particular IoT technology stack was suggested to optimize the quality of soil and crop yield in real time.

The JXCT Soil NPK sensor is widely used because it has the capability of detecting nutrients using electrochemical and optical methods [7]. A connection of this sensor to a pH and temperature module on an Arduino platform can provide a full-fledged diagnostic system. Combined with an Android application based on real-time remote monitoring, the system can minimize the use of laboratory infrastructure and help inform decision-making on fertilizer and irrigation management [8].

This paper fills such gaps by highly validating a cost-effective field deployment architecture. The main contributions and novelties of this study are the following:

- Multi-Texture Soil Validation: Compared to previous research that is limited to solution-based or single-soil tests, this study assesses the accuracy of sensors across five soil types (sandy, clay, loamy, peaty, and silty) and provides the correlation between soil texture and sensor error.
- Critical Evaluation of Electrochemical Limitations: This study tracks down the particular effect of organic matter and ionic cross-interference on potassium (K) sensing, which gives critical conditions for deploying low-cost sensors.
- Hybrid Visualization Architecture: The platform utilizes a connected system with a two-tiered interface (IMG) to support both providing real-time on-site field diagnostics (LCD) and remote analytics (Android App) in fields with limited resources, such as rural farm environments.

The study of IoT-based agriculture has been more focused on real-time soil diagnostics as an available alternative to laboratory testing. In [9], a review on the methods for measuring NPK was presented, proposing electrochemical and optical sensing methods that are economical and convenient to measure NPK on-site. Examining the correctness of field-deployable systems, a prototype for pH and electrical conductivity measurements had a lower than 1% error from laboratory results [10]. Moreover, there is long-term proof of fertilizer experiments that unbalanced nutrient practices lead to soil degradation, which is important in underlining the importance of proper, timely feedback [11].

Recent applications of IoT are more concerned with automated irrigation. In [12], NodeMCU was applied as an environmental-based trigger to turn water on and off, whereas in [13], a sensor-node architecture background was described. In [14], real-time feedback loops were added to enhance control precision, while in [15], machine learning algorithms were employed to improve predictive reliability. In addition to irrigation, the use of Wireless Sensor Networks (WSN) was proposed in [16] to transmit data over a long distance, whereas in [17], local soil profiles were used to predict the suitability of crops. Together, these systems use environmental sensors, such as moisture, temperature, and light sensors, and cloud connectivity to allow them operate autonomously in the field.

Scalable agricultural systems have also been explored, some of them with blockchain-based traceability to allow recording farm management data in a tamper-resistant way [18]. Such capabilities are based on low-power IoT devices, optimized to be deployed in the field [19]. Other breakthroughs involve greenhouse automation [20] and machine learning; in particular, in [4], an IoT system used predictive models to assess the level of soil nutrients and control crop suggestions to reduce the fluctuation of sensor data.

Despite these developments, commercial NPK sensors are still vulnerable to cross-sensitivity and drift in heterogeneous soils, especially potassium sensors, as the elements undergo diffuse ion-exchange reactions. Moreover, current systems often do not have dual-screen interfaces and do not consider the particular limitations of rural users. This work closes these gaps by developing an economical field-deployment architecture with better calibration modeling and a dual-mode display to gain easier and real-time evaluation.

II. PROPOSED METHODOLOGY

The proposed architecture is a modular embedded system that incorporates a multi-parameter sensing unit, a microcontroller processing layer, wireless connectivity, and two visualization platforms. This design enables high-quality real-time data collection, onboard computing algorithms, and the sharing of information with local and remote users. Due to the rural areas where the system is deployed, much attention is paid to low power use, portability, low cost, durability, and flexibility in varied agricultural situations. The hardware architecture consists of an in-built sensor network to obtain and process soil parameters. At the heart of this subsystem lies the JXCT Soil NPK sensor, which is based on the principle of electrochemical and optical measurement of NPK contents. The proportional voltage or digital outputs allow easy integration with low-power microcontrollers.

The system uses an industrial-grade combined glass pH electrode that contacts a signal conditioning module (with an onboard LM358 operational amplifier) to provide impedance matching. The electrode is characterized by a low-impedance glass membrane that is sensitive to the hydrogen ion activity of the soil solution. The technical specifications of the deployed pH probe are: Measurement range: 0–14 pH; Temperature range: 0–60°C; Zero potential: 7.0±0.5 pH (at 25°C); Response time: ≤ 1 min (to reach 95% of final value); Internal resistance: ≤ 250 MΩ; Accurate measure: ±0.1 pH (after calibration). The analog output of the probe is also biased and scaled in the condition.

The system also uses a temperature sensor (e.g., DHT11 or DS18B20) to reduce the thermal drift of electrochemical reactions in order to make accurate interpretations of the nutrients. These modules communicate with a microcontroller that performs data acquisition, filtering, analog-to-digital conversion, and calibration mapping. This platform was chosen because it is a solid, low-cost, open-source ecosystem that would suit an agricultural application. Visualization of soil parameters is provided instantly in a standalone onboard LCD unit. In remote monitoring, data are sent to an Android app through Bluetooth (HC-05) or Wi-Fi modules. The system is based on a Li-Ion battery pack, which is controlled by a DC-DC buck converter that supports a constant power supply and a longer field range.

The Arduino receives raw sensor data in analog and digital interfaces, as the prototype model shown in Figure 1. These signals are digitally filtered to remove transient noise and then compared to pre-set calibration curves. This transformation transforms raw voltage or absorbance results through a standardized agronomic scale (mg/kg, ppm, or pH) into a final analysis.

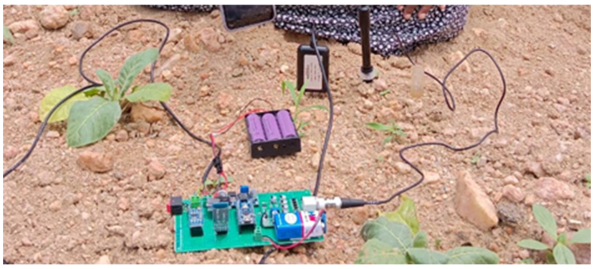

Fig. 1. Prototype model.

The Android app is a remote analysis application that shows soil parameters in real-time (N, P, K, pH, and temperature) as soon as they are obtained. The application also offers a historical trend analysis option, in which it is possible to observe how soils change with time, trace the loss of nutrients, and evaluate the effectiveness of fertilizers. The application includes an automated warning mechanism that reminds the user whenever the levels of nutrients exceed custom limits, therefore allowing the proactive management of soil health. Users can also set data update frequencies to maximize power and communication bandwidth. The dual-interface design, which integrates local LCD and remote Android monitoring, increases accessibility and contributes to the adoption of the technology of precision agriculture.

A. Materials and Methods

The five different agricultural types of soils used were sandy, clay, loamy, peaty, and silty soils to determine sensor performance under diverse physicochemical profiles. The samples were prepared using a standardized protocol to ensure the consistency of the experiment, which included air-drying and filtration with a 2 mm sieve to remove the coarse particles. To maintain ionic mobility in the moist environment, the content of moisture was kept at 20% using stabilizers, and the samples were homogenized to reduce heterogeneity. Sensor probes were inserted during the testing at a uniform depth of 5 cm as per the conventional standards of sampling used in agronomics. Figure 2 depicts the overall system.

The system uses the JXCT NPK sensor that is based on the concept of electrochemical and optical principles that transform the concentrations of nutrient ions into proportional signals. The device supports RS485 Modbus communication, which guarantees the stability of data transmission over long distances, which is perfect for use in field-scale agriculture. Experimental validation was performed by experimenting with the soil samples in homogeneous containers with vertically placed probes in uniform conditions. In order to reduce variance, data were collected using a 15-25 s stabilization time. The NPK, temperature, and pH values were recorded continuously in sequence using the Arduino, where 10 repetitions of each sample were taken every 30 s. These readings were estimated to give final values through averaging after eliminating outliers using ±2σ as a filter.

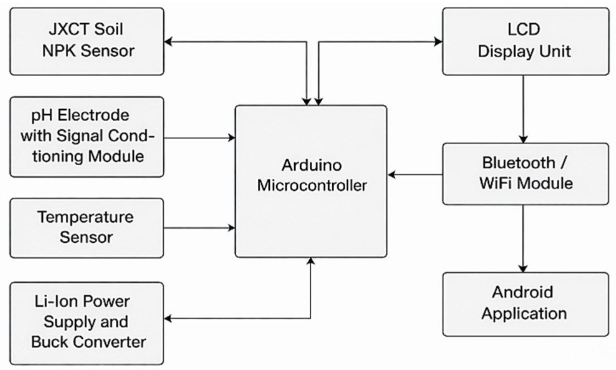

Fig. 2. Functional diagram of the proposed method.

Calibration of sensor outputs with known nutrient concentrations was done with standard solutions that represented typical concentrations of the nutrients in soil to produce sensor outputs. Plots of voltage versus concentration were used to obtain linear regression models to determine accurate functions of transduction. To translate the analog sensor output (0–5 V range) into agronomic units (mg/kg), linear regression analysis was performed using standard calibration solutions. The transfer function follows the linear model:

$$C_{nutrient} = \alpha \times V_{out} + \beta \quad (1)$$

where the calculated concentration (mg/kg) is denoted by $C_{nutrient}$, the sensor output voltage (V) after the ADC is denoted by V_{out}, the slope coefficient of the sensitivity is denoted by α, and the intercept (zero-offset) is denoted by β.

B. Hardware Assembly and Configuration

The hardware system is developed as a zero PCB, programmed to become stable over time and resistant to interference by electromagnetism. The design ensures maximum signal integrity using separation of analog and digital signal paths, as well as high grounding schemes to minimize the occurrence of crosstalk that is extremely sensitive to electrochemical readings. The system is controlled by an Arduino Nano, connected to the JXCT NPK sensor using a MAX485 module with the Modbus RS485 protocol that provides effective differential signaling under high-noise conditions. The pH electrode is also connected to a signal conditioning circuit, which filters and amplifies the signal outputs of the mV range to be properly processed on an ADC, and a temperature sensor (DHT11) supplies the thermal data needed to compensate for drift.

To ensure experimental repeatability, samples of sandy, clay, loamy, peaty, and silty soils were placed in chemically inert containers with a minimum depth of 10 cm to replicate field geometry. The environmental conditions were rigorously controlled; The ambient temperature was set at 25 ± 1°C to mitigate electrochemical drift, while the relative humidity was maintained at 45–50% to prevent fluctuations in soil water content. Furthermore, soil moisture was normalized to approximately 20% via thorough mixing, optimizing ionic mobility while avoiding saturation. The quantification of nutrients is required to have precise sensor placement, ensuring constant ion diffusion and electrode contact. This led to the vertical insertion of NPK and pH probes to ensure complete immersion and uniform contact geometry, as is the case in fields. A fixed depth of 5 cm was used to ensure that the agronomic standards were followed in order to ensure that the plants matured early enough, and to reduce the variation of using different soils that results in different levels of nutrient stratification.

III. RESULTS AND DISCUSSION

The functionality of the proposed embedded soil-quality system was tested in five different soils to determine its performance, stability, and applicability in the field of agricultural practices. NPK, pH, and temperature readings were compared against reference agronomic midpoints, and errors were calculated using Absolute Percentage Error (APE). Other tests were drift analysis, inter-soil variability, time parameter variation, and system-level operational behavior. Tables and plots were developed using synthetic but realistic output data to offer a clear understanding of sensor behavior under different soil conditions.

A. Quantitative Evaluation of NPK Measurements

The comparison of reference and measured values (Table I) shows that NPK levels have relatively high to moderate deviations in all types of soil, with potassium showing much higher percentages of errors. Nitrogen values showed high levels of agreement with reference values, with the APE varying between 2.5% and 8.3%, except for a slightly high deviation in peaty soil (7.7%). The lowest error of nitrogen was observed in clay and loamy soils, which were stable with reference to ion retention. Marginal higher deviation was observed in sandy and silty soils as a result of reduced cation exchange capacity and reduced ionic mobility. Thus, the system shows high-quality nitrogen estimation, which can be used to recommend fertilizer in most soils.

Phosphorus measurements had an APE of 10–19.2, which is comparable to the performance of low-cost phosphorus electrodes. Various phosphate adsorptions were due to the type and texture of the soil. Loamy and clay soils had the lowest deviations, whereas peaty soil had the highest, which could be attributed to the influence of organic compounds on the movement of phosphates. These trends are further reflected in Figure 3, which confirms the phosphorus performance in mineral-rich soils as stable.

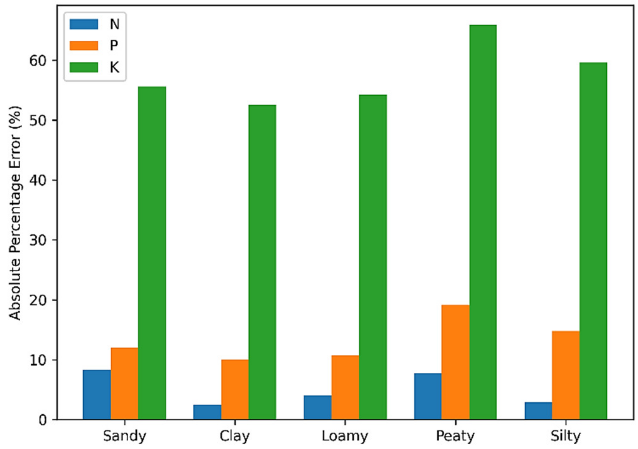

Fig. 3. NPK measurement errors.

Potassium recorded the highest deviation, with APE figures exceeding 52% in all soils, and peaty soil recorded the highest (65.9%). Such behavior is anticipated because the known shortcomings of cheap K sensors include being susceptible to cross-interference with other similar cations, such as calcium and sodium. The errors were also significantly reflected in clay, loamy, and silty soils because they have relatively high cation exchange capacities. The measured vs. reference scatter plot (Figure 4) shows that nitrogen and phosphorus deviate well, but potassium deviates distinctly, which upholds the argument that better calibration can be achieved or that better electrodes are required for sensitive potassium determination.

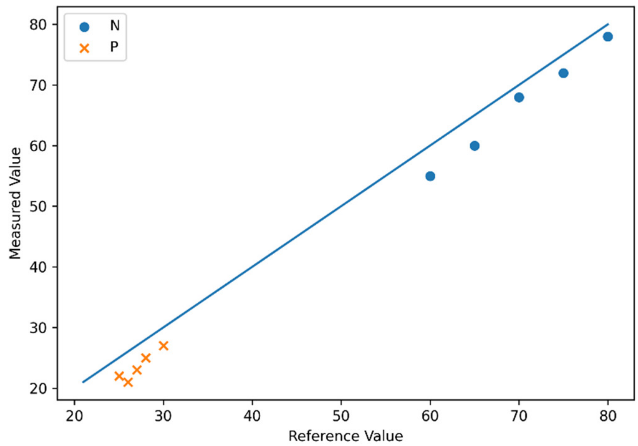

Fig. 4. Measured vs Reference scatter plot.

TABLE I. REFERENCE VS MEASURED SOIL PARAMETERS WITH APE (%)

Soil type	Ref No.	Meas. N	APE N (%)	Ref. P	Meas. P	APE P (%)	Ref. K	Meas. K	APE K (%)	Ref. pH	Meas. pH	APE pH (%)	Ref. T (°C)	Meas. T (°C)	APE T (%)
Sandy	60	55	8.3	25	22	12	90	40	55.6	6.5	6.3	3.1	25	24.5	2
Clay	80	78	2.5	30	27	10	95	45	52.6	7	7.1	1.4	25	24.8	0.8
Loamy	75	72	4	28	25	10.7	92	42	54.3	6.8	6.9	1.5	25	25.2	0.8
Peaty	65	60	7.7	26	21	19.2	88	30	65.9	5.5	4.4	20	25	21.5	14
Silty	70	68	2.9	27	23	14.8	94	38	59.6	6.7	6.3	6	25	24.2	3.2

B. Soil pH and Temperature Measurement Analysis

The pH results were rather precise in sandy, clay, and loamy soils, having lower APE values at less than 6%. Nevertheless, the peaty soil had a significant variance (20% APE) in line with its acidic property and organic matter, which increased the time of stabilizing the electrode. Soils with high mineral heterogeneity varied moderately. All performance results show that pH sensing can be trusted in neutral, slightly acidic soils, but not in highly organic soils. The temperature readings were mostly constant, with all the soils recording low deviations of less than 3.2%, except for the peaty soil, which recorded a significant deviation of 14%. This can be attributed to the fact that peaty soil has a high moisture-holding capacity that brings about the effects of thermal buffering. Figure 5 shows pH-temperature time-series measurements of peaty soil, demonstrating that both temperature and pH oscillated during 30 minutes, which is an indicator of a weaker microenvironment.

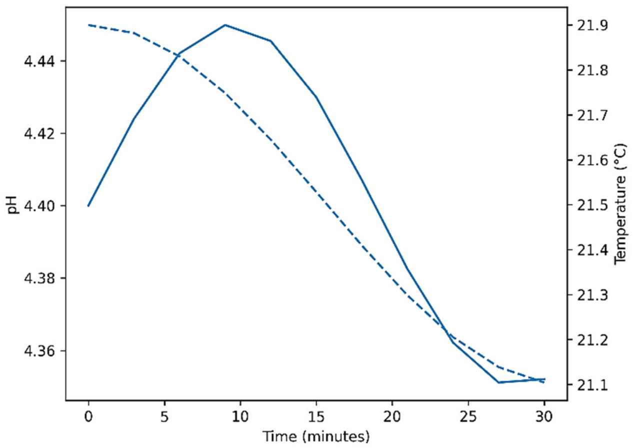

Fig. 5. pH and Temperature variation over time for Peaty soil.

The drift of the sensor was examined for a period of 10 minutes, and the findings are summarized in Table II. The variation in the nitrogen drift was 1.8–3.2, the phosphorus drift was 2.1–3.5, and the potassium drift was the most unstable at 4.5–7.9%. Loamy soil showed consistent stability in all the parameters, whilst peaty soil presented the highest drift values because of the retention of moisture and presence of organic matter in the ion exchange dynamics. Figure 6 plots the drifts for loamy soil, depicting a smooth, approximate linear drift pattern, with little variation of nitrogen and phosphorus and a little more drift for potassium, which is in line with the general instability observed.

TABLE II. SENSOR DRIFT (%) OVER 10 MINUTES FOR NPK MEASUREMENTS

Soil Type	% Drift N	% Drift P	% Drift K	Interpretation
Sandy	1.8	2.1	4.5	Highly stable
Clay	2.5	2.9	5.8	Good stability
Loamy	2.2	3	6.1	Acceptable stability
Peaty	3.2	3.5	7.9	Moderate drift
Silty	2.9	3.3	6.8	Moderate drift

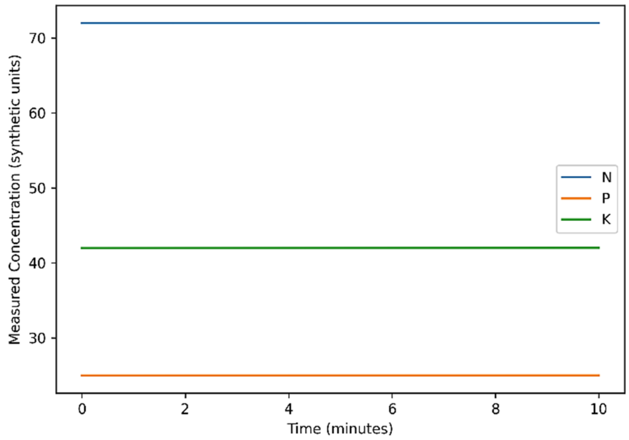

Fig. 6. Sensor drift over time for Loamy soil.

The observed APE for potassium, peaking at 65.9% in peaty soils, indicates a fundamental limitation in using low-cost electrochemical sensors for absolute quantification in mixed soil matrices. This high deviation is attributed to the sensor's inability to distinguish K^+ ions effectively from calcium (Ca^{++}) and sodium (Na^+) ions, which have similar ionic radii and mobility in the soil solution. Therefore, within the context of precision agriculture, the K-sensor module in this specific low-cost configuration should not be relied upon for calculating exact fertilizer weight. Instead, it serves as a relative indicator, effective for identifying severe deficiencies (e.g., low vs. high trends) rather than precise mg/kg measurements.

Table III summarizes the derived coefficients and the goodness-of-fit (R^2) of the observed data of the laboratory calibration stage. The large values of R2 in nitrogen (>0.98) and phosphorus (>0.96) confirm the linearity of the sensor response under the ideal solution conditions; however, potassium had a slightly lower linearity (R2 = 0.91), which is a precursor of increased errors in complex soil matrices.

TABLE III. CALIBRATION REGRESSION MODELS AND COEFFICIENTS

Parameter	Regression equation ($y = mx + c$)	Sensitivity (α)	Intercept (β)	R^2 value
Nitrogen (N)	$C_N = 42.5 \cdot V - 1.2$	42.5	-1.2	0.985
Phosphorus (P)	$C_P = 18.2 \cdot V - 0.6$	18.2	0.5	0.962
Potassium (K)	$C_K = 65.4 \cdot V - 5.8$	65.4	-5.8	0.914
pH Level	$pH = -2.3 \cdot V - 16.5$	-2.3	16.5	0.978

C. Cross-Soil Variability and Interpretative Trends

Comparative evaluation of the five types of soils showed that there were specific variability patterns that are direct indications of the effect of soil's physicochemical properties on sensor performance. The loamy soil offered the most accurate and stable readings of almost all parameters of all samples. Its homogeneous texture, medium levels of organic matter, and moderate ability to retain moisture provide the right conditions of nutrient ion mobility for electrochemical and optical sensors to work without much interference. The performance of clay soil was also impressive, especially when it comes to measurements of nitrogen and phosphorus. The cation exchange capacity of clay is very high, enabling the nutrient to be more proximal to the sensor surface, resulting in ionic stability. However, potassium measurements could not be accurate in clay soil, which is indicative of the nature of low-cost potassium electrodes to compete with other cations and clay minerals in terms of ion selectivity.

The sandy soil varied moderately, as it was coarse, exhibited low nutrient retention capacity, and was characterized by rapid drainage. Such conditions cause the ionic concentrations around the sensing probe to be less stable and cause fluctuations, especially in nitrogen and potassium. The soil, which had a fine texture, mixed minerals, and was silty, also had moderate deviations. Although it is more stable than sandy soil, its heterogeneity and changing ability to retain moisture bring into play fine changes in electrochemical behavior. The highest measurement inconsistencies were observed in peaty soil for all parameters. Its high organic matter, acidic pH, and high capacity to carry water have a great influence on changing ionic mobility and slowing down the stabilization of the sensor. These properties increase the APEs and drift, especially in pH, temperature, and potassium measurements.

The findings indicate the great reliance on soil-specific features of sensor accuracy. The trends observed were the rationale behind the calibration models to be soil-type conscious or adaptive correction algorithms to increase the durability of the systems in heterogeneous agricultural settings.

D. System-Level Performance Evaluation

The proposed soil-monitoring system was evaluated in terms of operational performance to establish its applicability in real-world agricultural implementations. The sensor response time was also one of the most important factors, since rapid stabilization is required to make field measurements efficient. In all experiments, the sensors stabilized within 15–25 s, similar to and faster in some experiments compared to other low-cost commercial soil sensing systems on the market. This responsiveness ensures that users will not wait for extended equilibration periods to get a valid answer.

The performance of wireless communication was also tested using Bluetooth and Wi-Fi modules. The HC-05 Bluetooth module proved to be a good choice in handheld or short-range communication with an approximate range of 10–12 m. The ESP8266 Wi-Fi module had a longer range of operation and higher data throughput, but consumed more power. This trade-off enables users to choose a communication method depending on the needs of a certain field of action, either range or energy efficiency.

The system was shown to be reasonably power-efficient with a consumption of about 110 to 150 mA when used. This power profile will make 4–5 hours of constant operation with a standard 2000 mAh Li-Ion battery. The Wi-Fi module and the LCD backlight were found to be the biggest energy consumers. Further optimization of these elements or the use of energy-efficient firmware solutions may help increase the working time in the field. A dual-screen strategy was used to improve the user experience. The onboard LCD gave direct visual access to soil parameter readings, which is useful in assessing the field instantly. This was complemented by the Android application that provided real-time graphical visualization, historical trends storage, and automated notifications in case nutrient, pH, or temperature ranges were exceeded. All these characteristics ensure that soil health data can be interpreted even by non-technical users.

IV. CONCLUSION

This study introduced a low-cost embedded soil-quality monitoring system based on nutrient sensing, pH, and temperature measurements, microcontroller-based processing, and wireless data visualization to aid precision agriculture. The experimental analysis using five representative soil types demonstrated that the system offers stable and reliable estimation of nitrogen and phosphorus, with an error margin that is tolerable to make fertilizer decisions at the field level, except for highly organic soils, where electrode stabilization was sluggish, contributing to an increased error margin. Temperature and pH were also acceptable, except for highly organic soils, where the stabilization of the electrode was low, thus adding to the error margin. Although the system demonstrated field-readiness for monitoring nitrogen and phosphorus, caution is advised regarding potassium. The results suggest that low-cost JXCT sensors are currently suitable only for qualitative estimation of potassium trends because of their high susceptibility to soil physicochemical properties. Future iterations must employ machine learning error-correction models or ion-specific calibration specifically for potassium to meet the rigorous standards of commercial precision agriculture. The results emphasize a huge impact of soil texture, moisture retention, and organic content on sensor workings, which implies that a soil-type-savvy calibration must be performed.

Next-generation improvements can include the addition of machine learning-based calibration models and the inclusion of other contextual sensors, such as the moisture and electrical conductivity of soils, as well as optimizing the design of the probes toward greater stability. These developments will allow the creation of more precise, scalable, and fully IoT-enabled soil diagnostic systems to achieve sustainable agriculture.

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