A Robust Wireless Sensor Network for Real-Time Soil Moisture Analysis in Precision Farming

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Abstract: A wireless sensor network (WSN) is designed to monitor soil moisture in real-time in precision farming, as demonstrated in this paper. This system enables farmers to make informed decisions regarding irrigation, water usage, and crop yield through the integration of advanced sensors and communication protocols. WSN architecture, design, and functionality, including node deployment, data transmission protocols, and sensor integration, are examined. Based on the results, the proposed system offers an ideal solution for large-scale agricultural monitoring, as it provides real-time soil moisture data with minimal power consumption. This system significantly improves data accuracy, scalability, and network stability, as demonstrated through extensive simulations and practical experiments conducted under various conditions. Our proposed system effectively addresses several critical challenges prevalent in agricultural Wireless Sensor Networks (WSNs), including enhanced energy efficiency, robust and reliable data transmission, and adaptive sampling techniques specifically designed for dynamic and unpredictable field environments. The network incorporates advanced, low-power capacitive soil moisture sensors integrated seamlessly with a novel hybrid routing protocol. This innovative protocol strategically combines both cluster-based routing and direct node-to-sink transmission approaches, thereby optimizing communication pathways, reducing overall power consumption, and maintaining stable network operation under fluctuating agricultural conditions. This integrated solution ensures accurate real-time monitoring, enabling improved decision-making and resource allocation in precision agriculture applications.

1 INTRODUCTION

WSNs, for example, are transforming traditional agricultural methods. Using these technologies, farmers can monitor and manage environmental variables with greater accuracy, enhancing crop yields, optimizing resource use, and improving overall farm management. As irrigation schedules, crop health, and water conservation efforts are all affected by soil moisture, precision farming has become increasingly important. The management of soil moisture requires farmers to have accurate, real-time data they can rely upon. Having a robust network of wireless sensors that can analyze soil moisture in real-time is essential. A sensor network tracks soil moisture levels continuously throughout farming field and transmits data wirelessly to a central system that analyses the data [1]. In addition to improving crop performance and reducing water waste, such systems provide constant, up-to-date information on soil conditions.

In order to be effective, a system like this needs to be reliable, scalable, and able to perform in real-time. As environmental interference, signal loss, and sensor failure can undermine data quality and accuracy, it is crucial to create a network that is energy-efficient and robust enough to operate in agricultural environments that are both diverse and harsh. An examination of such systems is provided, including sensor deployment strategies, data transmission protocols, energy efficiency, and system scalability. This paper focuses on leveraging WSNs to enhance agricultural practices, improve water efficiency, and promote sustainable development through the use of WSNs [2]. Remote monitoring of environmental, crop, and soil conditions would be necessary for such an undertaking. Sensor networks, also known as Wireless Sensor Networks (WSNs), enable this process by establishing wireless communication between a wide variety of sensors [3]. Microelectronic advances are expected to enable wireless networks (WSNs) to play a significant role in the Internet of Things (IoT) [4]

Scientifically, WSN applications in agricultural applications are considered state-of-the-art and not without reason. With the advent of accurate sensing and mathematical models, precise agriculture has taken on new horizons, enabling intelligent decision-making and improving productivity, reducing costs, and reducing environmental harm, all key enabling factors of smart farming [5]. Smart farming [6] and similar agricultural approaches not only deal with sensing but also with (i) data mining and visualization; (ii) a decision-support system, a modelling tool, and a planning tool; and (iii) Automated tools, monitoring robots, and online applications are part of the action. Producing large volumes of data within short periods can help producers predict crop damage and prevent it, a phenomenon that never ceases to decrease, possibly due to climate change [7], [8]. In other words, intelligent agriculture is more than a passing trend; it is part of a multidisciplinary approach to agricultural production described by [9], [10].

While these emerging technologies offer many opportunities [11], there are also many challenges since they are still in their infancy. An example of one such challenge is synchronization, which is often required in networking environments, but especially in distributed environments [12], [13]. When remote nodes are synchronized to provide time-correlated measurements, the end-user or application will be able to successfully interpret and use the latter to make decisions when the individual data is processed or fused to create a new set of information [14]. Depending on both the hardware and software utilized, accurate synchronization can be challenging due to multiple delays, which can accumulate over time [15].

2 LITERATURE REVIEW

Over the past few years, the concept of utilizing Wireless Sensor Networks (WSN) for precision farming has gained considerable attention. Specific applications include soil moisture monitoring, which is crucial to optimizing irrigation systems and improving water efficiency. In agriculture, robust WSNs adapted to real-time soil moisture analysis have been developed through a number of research studies and technological advancements [16]. A review of key works related to real-time agriculture applications and WSN-based soil moisture monitoring is presented. Using an intelligent humidity sensor and a low-power wireless Transceiver, [17] proposes an irrigation management system that collects data and records SWT to facilitate irrigation [18]. In this paper, we used laptops, computers, or personal digital assistants as monitoring devices. SWT data processing enables soil moisture trends to be determined, as well as irrigation schedules to be predicted and modified to improve crop production. The automatic irrigation controller described in [19] is an open loop system, which is automatic and adaptive. A soil moisture measurement system determines how much water is necessary to maintain the soil moisture so that just the right amount of water is provided to the crop. A microcontroller controls pumps and relay switches.

A wireless soil moisture sensor based on fringing electric field (FEF) - capacitance mode will be designed, manufactured, and tested for the purpose of determining soil volumetric water content (VWC) [20]. Permeability, signal strength, sensitivity, and linearity are some of the performance criteria used to evaluate a sensor's performance. By using wireless multimedia sensor networks, Precision Agriculture Sensing System (PASS) meets the needs of modern precision agriculture. This system can sense a large farmland without the need for human intervention. With the sensor node, a wireless multimedia sensor network can be built in a matter of minutes. Using a bitmap index, a reliable data transmission mechanism is proposed for bulky data transmissions. Bulky data can be transmitted reliably using an index bitmap mechanism. The sensor node will be powered by a battery system that switches between arrays. In a comprehensive experiment and a large-scale deployment in the real world, PASS has been evaluated for its effectiveness and performance [21].

Wireless sensor networks (WSNs) or satellite imagery are currently used to estimate soil moisture, but these methods are expensive and not very accurate [22]. Research has utilized all types of sensors, both above-ground and underground, to overcome these limitations while increasing the reliability of analysis and predictions. A soil moisture prediction system was developed by Author [23] using ambient temperature, humidity, and soil moisture sensors. After implementing a smart sensor node, the authors used the Message Queue Telemetry Transport (MQTT) protocol to connect it to the cloud platform. Despite these limitations, the method is economical, and multiple sensors improve the accuracy of measurements over a wide area of land. The reason for these limitations can be attributed to two factors: first, it is economically expensive to use soil moisture sensors. As another restraint, there may be sensor failures, most likely because of their greater quantity and measurement errors as a result of hostile environmental conditions and incorrect installation.

A support vector machine (SVM) can also be used to predict soil moisture with digital photography [24]. However, hardware costs and size may make a photography-based approach unfeasible in some cases. This paper presents another method based on soil pictures [25]. It is investigated how soil moisture can be predicted using various machine-learning methods. There is a remarkable overview of machine learning approaches presented here, but RNNs and their improvements, such as LSTMs, are not discussed. In [26] compares multiple linear regression, support vector regression, and random forest algorithms, assessing their effectiveness for soil moisture prediction [27].

3 METHODOLOGY

3.1 Network Architecture

The TelosB wireless sensor module connects soil moisture sensors, soil temperature sensors, or soil humidity sensors to the network nodes. During the measurement cycle, each node collects data about soil moisture, relative humidity, and soil temperature, which is then sent to a sink node for analysis. The following architecture is proposed to accomplish this goal.

Sleeping and waking up periodically is essential for the sensing motes to extend the network's life. Network operations are ongoing. Most of the time, the nodes are sleeping (the sleep period lasts 26 minutes, the wake-up period lasts 4 minutes, and the time between two consecutive periods lasts 4 days). There will be a lot of sleep among the sensor nodes during the day. To initiate the transmission of a message, the destination node must also become active (wake up) when the source node becomes active (wake up). A periodic synchronization of nodes is necessary to coordinate this process, as explained in section II-C. As data is relayed from nodes further up the tree, nodes near the sink node will drain their batteries more quickly. A lack of precautions may lead to nodes near the sink node dying much earlier than those in the bottom layers. To make all the nodes' energy consumption consistent, a new SPT should be calculated, considering that a greater number of energy-consuming nodes will be chosen as parents with a larger number of children.

Sensor networks that monitor environmental conditions, such as soil moisture, usually perform convergence casting. Data is gathered from all sensor nodes and stored at sink nodes with a tree-based routing architecture [10]. There are two types of convergent casts: aggregated data and raw data. At each hop, aggregated convergence casting uses data aggregation techniques, whereas raw data convergence casting relays sensor readings directly to the sink. Whenever parameters are highly correlated, an aggregated converge cast is used to detect them.

We designed our soil moisture sensor network not to be densely deployed, so it covers a large area with few nodes, making it an affordable solution to monitor soil moisture. In this situation, it is assumed that all sensor readings are shared equally between the sink and source nodes.

Coordinated, comprehensive, and sustained Earth observation strengthens the capacity of the international community to achieve this.

In precision agriculture, environmental conditions related to crop health can be monitored using ZigBee wireless communication [28]. Wireless connectivity is provided by IEEE 802.15.4. ZigBee was originally developed for personal area networks under the ZigBee alliance [29]. Besides its flexible network structure, it comes with a long battery life, provides mesh, star, and tree topologies, and supports multi-hop data transmission.

A prominent IoT application that uses BLE is agriculture, which is a suitable protocol for Bluetooth smart technology [29]. The device was designed specifically for IoT applications requiring low bandwidth, low latency, and short range. With BLE, you can connect unlimited devices faster, use less power, and setup is easier than with conventional Bluetooth. In its original form, 6LoWPAN is an IP-based communication protocol for IoT applications. The low bandwidth and low power consumption of 6LoWPAN also make it a low-cost network. 6LoWPAN, including star and mesh topologies, supports multiple topologies. A network adapter layer is used between the network and the MAC layer to ensure that IPv6 and IEEE 802.15.4 are interoperable [29].

3.2 Soil Moisture Sensor Based on Coils

Using the mutual inductance principle, this study proposes a sensor consisting of sensors. According to this principle, a magnetic field will be generated whenever an electric current (EC) is applied to a powered coil (PC). Several parameters influence the magnetic field of a coil, including the number of spires (N), the diameter of the wire, and the diameter of the powered coil (PC), as well as the signal used to power the coil (including voltage and the). An electric coil's magnetic field is determined by a variety of factors, such as the number of spires (N), the diameter of the wire, and the signal used to power the coil (voltage and frequency). The (1) depicts how Ampère's circuital law determines a solenoid's magnetic flux density B as a function of the permeability of the core, N spikes, and I intensity. Although (1) applies to a free space infinite solenoid, in our case, we have a soil solenoid with relative permeability μ_r. As shown in (2), the solenoid's length l should be considered. Our soil's μ_r is modified when the moisture changes, which results in a change in its magnetic field generated. Increasing moisture will increase the soil's permeability. This will increase the magnetic field. Solenoid cores are generally placed in the centre, where the magnetic field is greatest. As a result of the powered solenoid's magnetic field being higher in the centre (with different moisture levels in different tests), the soil will be the core of our device.

$$B = \mu_0 NI, \tag{1}$$

$$B = \frac{\mu_0 \mu_r NI}{l}. \tag{2}$$

An induced magnetic field will be created if another coil is in close proximity to the PC. Mutual inductance refers to this phenomenon. Magnetic flux will be created by the lines going through the induced coil (IC) from the PC's magnetic field. According to the theory, mutual inductances are as follows to (3), the mutual inductance of two solenoids is M. A coil has an inductance $L1$ and, an inductance $L2$, and a coupling coefficient k. Equation (4) shows that $L1$, L2, N, l and a depend on the core $\mu_0 \mu_r$. As before, the result of mutual inductance is determined by the medium acting as a core, the soil. A soil's permeability affects its K. A perfect coupling causes K to be maximum (1), while an absence of inductive coupling causes it to be minimum (0). A value of k indicates that 100% of the lines of flux in PC will cut all the turns in the IC, so the soil is highly conductive, and the coils are perfectly symmetrical. As part of our experiments, we examined the core's permeability (the characteristics of the core). Furthermore, different prototypes (different N 1 and A) are tested for various geometries to determine how they affect performance. While coils are located in the same place in each prototype, PC and IC distances, as well as total coil lengths, differ.

$$M = k\sqrt{L1, L2,} \tag{3}$$

$$L1 = \frac{\mu_0 \mu_r NA}{l}. \tag{4}$$

3.3 Circuit Design

Figure 1 illustrates the circuit design for the soil profile moisture sensor. Circuits for sensor acquisition and control were essentially the same. Moisture acquisition circuits include annular metal electrodes, voltage-controlled oscillating circuits, amplifiers, and frequency dividing and conditioning circuits to measure soil moisture. An ATmega328p 8-bit microcontroller (MCU) is integrated with the sensor control circuit, as well as an NRF 24L01 wireless 2.4 GHz communication module and a time-sharing power supply circuit in addition to the battery powering the sensor, a solar panel supplied 7.4V output from a lithium battery.

This means that signal processors divide, condition, and shape frequency signals in order to be measured directly by MCUs, that is, frequency division and conditioning. Depending on the soil moisture content, equivalent capacitance varies. In the voltage-controlled oscillating circuit, output high frequencies are measured between 100MHz and 150MHz. The frequency divider circuit, as well as the circuit that converts high-frequency signals into low-frequency signals, is required for the microprocessor to read the measured output frequency. The original frequency signals were divided by 64 using a dual-mode pre-scaler and divided by 256 using an SN74HC393D digital chip. MB504 and SN74HC393D are typical frequency-dividing circuits that enable back-end processors to measure frequency signals directly. Texas Instruments has developed a dual four-bit binary counter with an SN74HC393D. The number of counts can reach 256. When 256 signal pulses are input, the output will flip, and the input frequency will become 256.

3.4 Network Design

During the Southern Sierra Critical Zone Observatory (CZO) (374' N, 11911' W), a 1.5-kilometer transect was surveyed along 23 locations to monitor water balance variables. There is a transition zone between rain and snow, with low elevations receiving more precipitation in the form of rain. In this sub-catchment of KREW, most precipitation falls, such as snow, in the northern part. There are 76–99% mixed-conifer forests in the catchment, mixed chaparral, and barren areas in WSN-instrumented catchments.

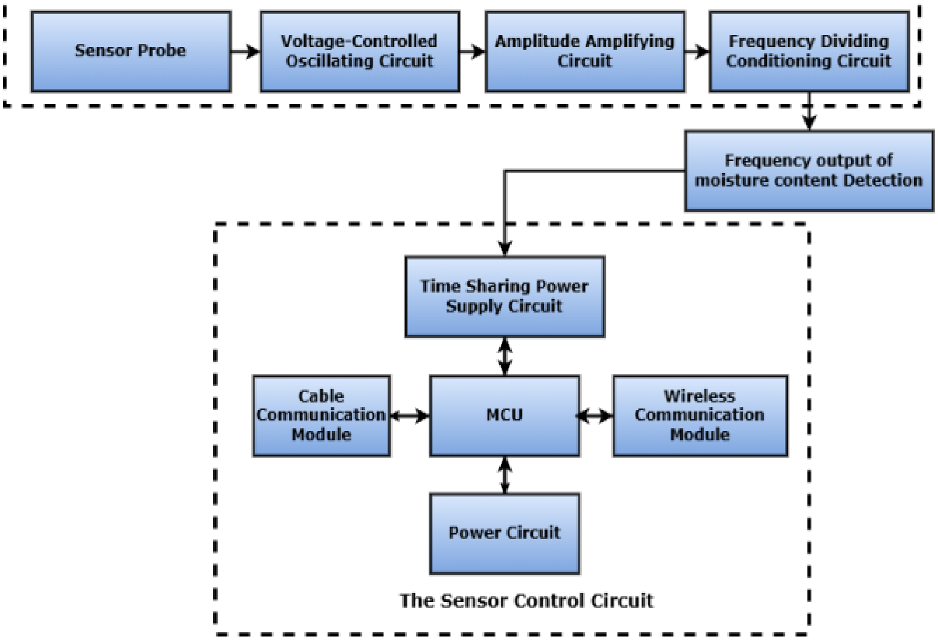

Figure 1: Principles behind the design of the soil profile moisture sensor.

As far as the network level is concerned, regular WSNs have the same function for all nodes. After measuring a parameter, each node processes it and then sends its findings to its neighbours. By sending sensed information to its neighbours, the base station or sink will be able to receive it. As opposed to passive WSNs, passive WSNs receive data from their environment and send it to a sink without any further processing. An active WSN will notify the sink and/or the management centre whenever an event occurs. It is then the responsibility of a few nodes to take action (send the information to other nodes, sense more variable information, etc.) as a result of the notification (or selection) of a few nodes.

There is a need for intelligent WSNs in many environments since passive WSNs are not useful. An event may require certain actions to be taken within a WSN to respond appropriately. A WSN used to detect fire, for example, should be able to measure a variety of variables to verify and even monitor the fire's progress. Once these variables are collected, a sensor may transmit the information to a node with a higher processing capacity to activate fire fighting mechanisms.

4 RESULTS AND DISCUSSION

Based on a 0.5 m emitter height, various deployment configurations were tested with a receiver at various heights. X-axis numbers indicate tree positions. For all distances tested, the receiver positioned closest to the ground consistently produced higher RSSI values, proving to be the most stable configuration (Fig. 2). Trees 1 and 4 showed minor fluctuations, while trees 2 and 4 showed more significant fluctuations due to the density of foliage there. The multipath effect is likely to be responsible for these fluctuations.

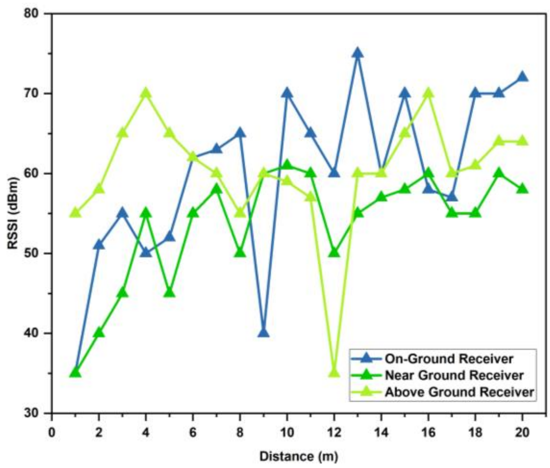

Figure 2: RSSI (dBm) versus distance (m) at 0.5 high emitter.

This Figure 3 shows the resonance frequencies (in kHz) and induced coil voltages (in mV) of the prototypes developed.

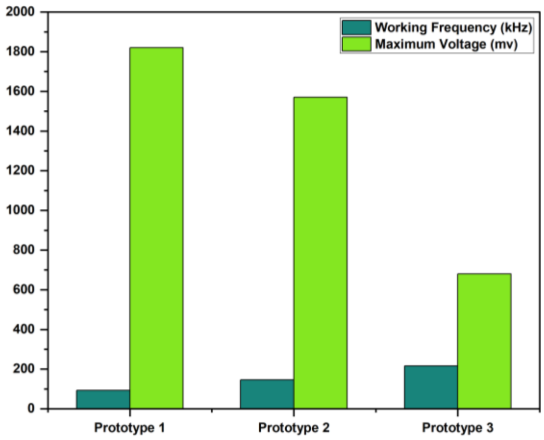

Figure 3: Moisture measurement prototypes.

Figure 4 shows the results of Prototype 1, showing 93 kHz working frequency and 1.82% maximum output voltage. As soon as the best sensor has been chosen, it is tested on several soil types to assess its versatility, aiming for maximum linearity. In the previous figure, linear behaviour is observed up to a humidity level of 18.75%, which corresponds to 750 mL of water for 4000g of sand. Sand on a beach is less sensitive than soil on a farm, so this needs to be considered when processing real-world results.

Figure 5 shows the results for a 1-meter-high emitter. A near-ground receiver best achieves performance. There is a reduction in signal quality between trees 2 and 4 in this scenario. However, after passing through a densely forested area, the near-ground receiver recovers its signal quality. There is no difference between the above-ground and below-ground deployment in areas with dense foliage, but there is a significant difference in signal quality in other areas. In addition, the on-ground receiver configuration performs poorly.

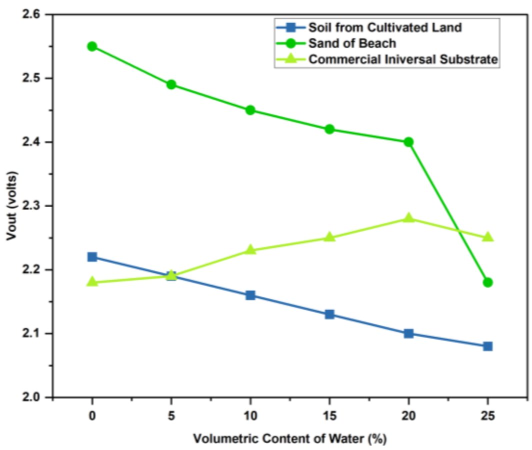

Figure 4: Various soil types and prototype 1's behaviour.

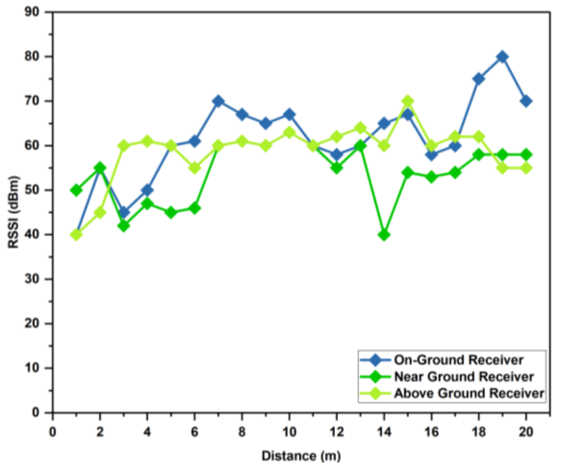

Figure 5: RSSI (dBm) versus distance (m) at emitter at height of 1 m.

Using a 1.5 m emitter height, Figure 6 illustrates the results. Almost all measurement points provide the highest level of signal quality, although there are some fluctuations between trees 2 and 3. This configuration maintains superior signal quality despite these fluctuations. In addition to near-ground receivers, above-ground receivers offer a more stable signal, but their quality still falls short. As a result of the on-ground deployment, the results were the poorest and fluctuated the most. A higher emitter height yielded a lower average signal quality than a lower emitter height, also worth mentioning.

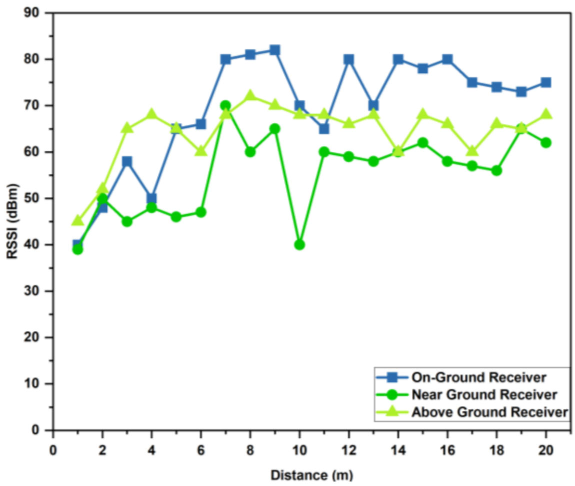

Figure 6: RSSI (dBm) versus distance (m) at 1.5-meter-high emitter.

The result at 2 meters is shown in Figure 7. All other emitter heights yield poorer signal quality than this one. Near-ground deployments deliver the best results, as with previous cases. At this emitter height, however, all receiver configurations display similar performance. The on-ground configuration continues to be the least effective option in all scenarios.

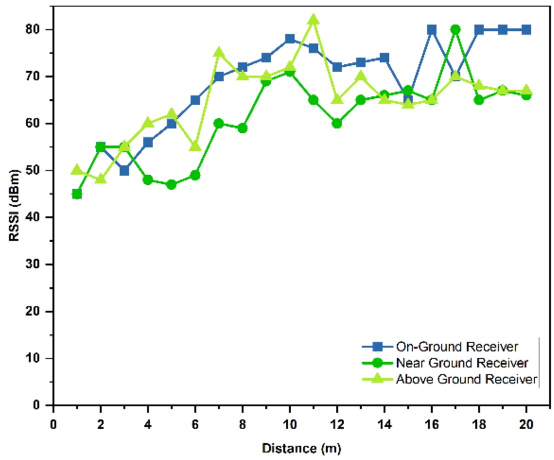

Figure 7: RSSI (dBm) versus distance (m) at emitter at height of 2 m.

5 CONCLUSIONS

As a reliable method for optimizing water use and improving agricultural productivity, WSNs have been integrated into precision farming to monitor soil moisture. The proposed system introduced in this paper, which integrates an energy-efficient architecture with periodic sleep-wake scheduling strategies and effective communication protocols, demonstrates significantly enhanced performance compared to existing agricultural monitoring systems. By deploying low-cost, highly responsive soil moisture sensors coupled with optimized routing techniques, the system achieves robust performance in large-scale agricultural environments, while ensuring minimal energy consumption and extended operational lifetimes. Future advancements should focus on scaling the system to handle more complex, heterogeneous agricultural scenarios, including diverse crop types, varied field topologies, and unpredictable environmental conditions. Additionally, enhancing sensor node reliability and durability would further ensure consistent and uninterrupted data collection. Integration of emerging technologies, such as cloud computing platforms for comprehensive data storage, analytics, and artificial intelligence for sophisticated predictive modeling, could greatly enhance real-time data interpretation, streamline decision-making processes, and ultimately improve agricultural productivity and resource efficiency in farming applications.

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