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Optimized resource management system for precision farming using cluster based wireless sensor network

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ABSTRACT

The deployment of wireless sensor networks (WSNs) in precision agriculture is essentially guarded by the energy limitations of sensor nodes, which can impede long-term, autonomous field monitoring. This paper introduces a hierarchical, cluster-based resource management system intended to prevail over these limitations. The central part of our approach is a dynamic clustering algorithm that intelligently groups sensor nodes to balance energy consumption and streamline data transmission across the network. Within each cluster, intra-cluster data aggregation is performed to fuse raw sensor data—encompassing critical parameters like soil temperature, humidity, and pH—thereby minimizing redundant packet transmissions. This aggregated data drives a predictive control model that automates decision-making for the precise actuation of irrigation and fertigation systems. Empirical validation demonstrates that our methodology achieves a dual objective: it significantly extends the network's operational lifespan by enhancing energy efficiency and throughput while reducing latency. Concurrently, this optimized resource allocation directly correlates with increased crop yield, presenting a robust and scalable framework for sustainable, high-efficiency agriculture, particularly in resource-intensive environments like urban and vertical farms.

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1. INTRODUCTION

The 21st century presents humanity with a complex and interconnected set of challenges, at the heart of which lies the critical task of ensuring global food security. The global population is projected to grow continuously, surpassing 9 billion by 2050 that places unprecedented demand on our agricultural systems. This demographic pressure is compounded by escalating environmental concerns, including climate change, increasing water scarcity, soil degradation, and the loss of biodiversity. In this context, the traditional agricultural paradigm—characterized by uniform, field-wide resource application—is proving to be increasingly unsustainable. It often leads to the inefficient use of vital inputs such as water and fertilizers, contributes to chemical runoff that pollutes ecosystems, and fails to maximize the genetic potential of modern crops. This confluence of pressures necessitates a fundamental shift towards more intelligent, efficient, and environmentally conscious farming practices, often referred to as Agriculture 4.0 [1] or the Fourth Agricultural Revolution.

Precision farming (PF) stands at the vanguard of this transformation. It is an advanced agricultural management philosophy that recognizes and responds to intra-field variability [2]. Instead of treating a field as a homogenous unit, PF employs a suite of technologies to gather, process, and analyze data at a granular level, enabling site-specific application of resources. The core objective is to achieve a multi-faceted optimization: enhancing financial returns for the farmer, drastically cutting down on waste, and mitigating the adverse environmental effects of farming operations [3]. Historically, the technological backbone of PF has consisted of the global positioning system (GPS) for precise location tracking, geographic information systems (GIS) for managing and visualizing spatial data, and remote sensing (RS) via satellites or drones to monitor crop conditions from afar [3]. This combination allows for practices like variable-rate fertilization, precise seeding, and the creation of detailed yield maps.

Furthermore, these methods often still rely on considerable manual labor. Practices like grid soil sampling, while more precise than whole-field analysis, are physically demanding, time-consuming, and provide data at a relatively coarse spatial and temporal resolution. The creation of application maps was often a manual process, requiring expertise in GIS software and agronomy [3]. This combination of high capital investment, operational latency, and labor intensity makes traditional PF economically unviable for a large segment of the world's farmers, particularly those with small or medium-sized holdings. These drawbacks highlight a clear and pressing need for a technological solution that is more automated, cost-effective, responsive, and capable of providing continuous, real-time insights directly from the ground level.

In response to these pronounced limitations, wireless sensor networks (WSNs) have emerged as a disruptive and enabling technology poised to revolutionize data collection in agriculture [4]. A WSN is a complex network of many low-cost, energy-efficient sensors distributed over a specific location. Each node is a miniature, self-contained system, typically equipped with a sensing unit to measure parameters like soil moisture, ambient temperature, and humidity; a microcontroller for local data processing; a wireless transceiver for communication; and a power unit [5]. These nodes collaborate to form an intelligent network, gathering data and relaying it wirelessly to a central base station (BS) or a remote server for analysis and decision-making [6].

The application of WSNs directly addresses the core deficiencies of conventional PF. By embedding sensors within the agricultural land, WSNs facilitate a highly automated, ground-level monitoring system that operates in real time. This empowers farmers to transition from reactive, calendar-based management to a proactive, data-driven approach. For instance, irrigation can be triggered precisely when and where it is needed based on continuous soil moisture readings, conserving immense quantities of water [7]. Similarly, localized changes in temperature and humidity can act as an early warning system for fungal diseases, allowing for targeted pesticide application that minimizes chemical usage and its environmental impact. Furthermore, the inherent heterogeneity of WSNs allows for the creation of a tailored monitoring ecosystem, where different types of sensors can be deployed according to the specific needs of the crop and the economic constraints of the farm [8].

While the potential of WSNs in PF is immense, their practical, long-term deployment is critically dependent on solving one overarching challenge: energy efficiency [9]. The sensor nodes are typically battery-powered and distributed across vast fields where manual battery replacement is logistically complex and financially prohibitive. The energy consumed during sensing, data processing, and most significantly, wireless transmission is the primary factor limiting the operational lifetime of the network. An unmanaged WSN can deplete its energy reserves rapidly, rendering the system unreliable and economically unsustainable.

Therefore, the central motivation for this research is to design and develop an intelligent and comprehensive resource management framework specifically for WSNs in agricultural applications. The goal is to maximize the network's operational longevity while ensuring the timely and reliable delivery of high-quality data. To address this multifaceted challenge, this research delineates the following specific objectives: i) to develop a novel precision agricultural methodology that integrates advanced WSN management techniques to enhance crop productivity while minimizing energy consumption, ii) to propose an innovative clustering strategy for the WSN, which will organize sensor nodes into logical groups to optimize data aggregation and create energy-efficient communication routes to the BS, and iii) to implement an improved resource management system that intelligently utilizes techniques such as energy-aware routing protocols and adaptive duty cycling (alternating between active and sleep modes) to drastically reduce overall energy usage. To introduce an innovative classification method for the accurate analysis and interpretation of the collected sensor data, enabling more effective and automated farm management decisions.

This research endeavors to deliver a holistic, integrated system that moves beyond theoretical concepts to provide a practical solution for modern agriculture. The primary contribution will be a synergistic framework where a novel clustering algorithm forms an energy-efficient network topology, an advanced resource management system operates upon this structure to prolong its life, and a sophisticated classification method acts as the intelligent core for agronomic decision-making.

The successful realization of these objectives is expected to yield a highly programmed agricultural system characterized by its autonomy, efficiency, and sustainability. The efficacy of the proposed approach will be rigorously evaluated through simulation and comparison against existing state-of-the-art methods. The performance will be benchmarked using critical network metrics, including throughput (rate of successful data delivery), network longevity (operational lifetime), energy consumption, and end-to-end delay. Ultimately, this work aims to demonstrate a scalable and economically viable model for WSN-based PF, contributing a significant step towards achieving the dual goals of enhanced agricultural productivity and environmental stewardship.

The remaining part of the paper has been organized as follows: section 2 highlights the beneficial aspects as well as downsides of the many works that are reachable in this field of study. The proposed approach is described in section 3, along with the essential algorithmic steps and an explanation. The outcome of the proposed approach is illustrated in section 4, and the research is concluded with an analysis of its outcomes in section 5.

2. LITERATURE REVIEW

The effective implementation of WSNs in PF is critically dependent on robust resource management, as this directly dictates network longevity, operational cost, and the reliability of data collection. A significant body of research has been dedicated to tackling this challenge. Accordingly, this section presents a comprehensive review of the existing literature, surveying the key contributions and methodologies proposed by various researchers. It examines the different approaches to energy conservation, data routing, and node clustering that form the foundation of resource management in WSN-based agricultural applications, thereby contextualizing the novel work proposed in this study. The technology that supports for digital greenhouse systems was analyzed by the author in [9] within the framework of smart agriculture. The five main levels of on-site and remote surveillance, collecting data, communication services, and related product traceability information were all systematically reviewed. This served as the foundation for the development of an extensive array of ZigBee WSN-based agricultural digital greenhouse technologies.

The ability to collect data and transmit it to a central hub in real-time offers significant benefits, including better management of latency and network traffic through optimized unmanned aerial vehicle (UAV) flight paths and on-site data processing. In related work, reference [10] outlines a hierarchical structure for precision agriculture where WSNs and UAVs collaborate for crop monitoring. This combination of intelligent WSNs, internet of things (IoT), and UAVs has become a trustworthy method for control, information gathering, and decision-making in specialized fields. To address energy consumption, the author in [11] focused on balancing and reducing power usage in WSNs. They created a distributed energy region method to designate nodes with high energy reserves as source routers. This system determines the optimal transmission path for other nodes by calculating an "effective distance" and then applying an ant colony optimization algorithm to find the most efficient route.

Parganiha and Kumar [12] introduced a novel cluster-based routing method that uses neuro-fuzzy rule-based clustering to achieve cluster-based routing and improve network efficiency. Cluster formation in WSNs, according to this technique, uses energy modeling for efficient packet routing using CNN and fuzzy rules for weight adjustment to provide efficient packet routing which extends the lifespan of the network. An intelligent routing method based on deep reinforcement learning (DRL) was created by the author in [13]. It greatly lowers latency and extends network lifespan. The recommended approach divides the whole network into several unequal groups based on the data load that is now present in the sensor node, thus reducing the likelihood that the network would die too soon. An extensive test of the suggested approach is conducted using ns3.

Mehedi *et al.* [14] demonstrates the application of remote sensing data for predicting crop yields, evaluating soil and plant nutrient levels, assessing crop moisture, and managing weed populations. By identifying the capabilities and limitations of these methods, future research can aim to develop more robust and effective decision-support platforms that boost farm profitability while ensuring environmental stewardship. To address the increasing global food demand and reduce agricultural labor, the authors in [15] presents an intelligent greenhouse management platform based on the IoT. The system leverages a cost-effective WSN that uses radio frequency (RF) to gather essential environmental data, such as temperature, humidity, and soil moisture. This data is then sent to a Raspberry Pi processing unit, which employs a fuzzy logic controller (FLC) to analyze the combined information and make smart, automated decisions regarding climate and irrigation control. For remote access and oversight, a human-machine interface (HMI) was developed on IBM's Node-RED server, allowing users to monitor the greenhouse from anywhere. Additionally, all collected data is stored in a MySQL database for historical review, ongoing monitoring, and refining control strategies, with test results confirming the platform's overall effectiveness and success.

Support vector machines (SVM) and artificial neural networks (ANN) were used in a comparative research [16] to predict soil water needs via quantifiable soil parameters for PF. According to the study's findings, the three-variable SVMs outperformed the eleven-variable ANNs in terms of accuracy. However, because of the large soil matric potentials that resulted mostly from relative errors, the correlation among the measured and the projected water content of the soil was comparatively lower with SVM. According to [17], the use of visual data mining technology in the agricultural sector application involves breaking down high-dimensional agricultural field measurements into smaller dimensions in order to extract crucial information about PF productivity, such as fertilizer and water applications. Sammon's mapping approach and self-organizing maps are used to break up the enormous database into smaller, understandable information so that decisions may be made quickly and intuitively. This study report concludes that self-organizing maps work well with enormous amounts of information, whereas Sammon's mapping approach works best with small amounts of information.

Pydipati *et al.* [18] implemented a crop pest management solution using color textural analysis to determine if classification methods could successfully detect diseases on citrus leaves. The paper explored the use of the ANN classification method, specifically using radial basis function (RBF) networks to yield fuzzy outcomes that represented the classification's strength.

Saadallah *et al.* [19] mentioned that WSNs are widely used in manufacturing automation and environmental surveillance. WSNs need to be cost-effective as sensor nodes have limited batteries. Low-energy adaptive clustering hierarchy (LEACH) facilitates the collection of energy-efficient information by WSNs. Cluster heads have an impact on network lifetime and LEACH protocol energy usage. In this research, the genetic algorithm is used to optimize the cluster head (CH) selection in the LEACH procedure. Cluster heads are selected by the software to optimize network energy efficiency. In the genetic model of the genetic algorithm, cluster heads stand in for solutions. Performance is measured by energy efficiency, and performance is increased by crossover, mutation, and selection. They tested the suggested method through thorough simulation. They contrasted the original LEACH methodology, LEACH-GA, and other optimization techniques. In comparison to other routing protocols, such as LEACH-C, FIGWO, GA-LEACH, PSO, ABC-SD, CGTABC2&ACO, LEACH, I-LEACH, and I-LEACH, this research demonstrates a 100% increase in network a long lifespan.

A technique called improved energy-efficient cluster head selection (IEECHS) is suggested in paper [20] for use in heterogeneous WSNs. In order to improve network performance and extend the lifespan of the WSN, the IEECHS algorithm integrates rotation-based clustering and energy-saving techniques, addressing the crucial concerns related to safety and energy consumption. The full duplex medium access control protocol (FDMAC) has been developed for the distributed network model employing the full duplex capabilities of nodes and the cut through mechanisms. It: i) offers channel usage prioritization to various categories of traffic and ii) is a contention window-based approach to recognizing collisions.

The primary aim of energy harvesting wireless sensor networks (EH-WSNs), as explained in [21], is to maximize operational efficiency in environments where scarce resources restrict energy harvesting (EH). Recognizing that traditional WSN routing approaches often neglect EH considerations, this study proposes a multi-hop, clustered routing protocol that is specifically designed to utilize renewable energy for EH-WSNs. The proposed approach uses energy conditions and the amount of collected energy to accomplish both centralized and decentralized clustering. Cluster creation, data transmission, and centralized administration are the three stages of the protocol's operation. We examine three different situations with various settings in order to assess the efficacy of the suggested method. The results demonstrate that despite enabling a greater number of nodes to remain functioning, the proposed method significantly reduces the overall network energy consumption. Together, the findings demonstrate that the recommended approach consistently increases network stability and efficiency across all evaluated scenarios.

Afzal *et al.* [22] mentioned that WSNs and emerging technology proliferate rapidly, network management is more challenging since it impacts the wireless networks' overall effectiveness. Conventional clustering was formerly used in WSN to overcome this constraint; however it became clear over the years that successful WSN effectiveness is impossible without an efficient method for cluster creation and CH choice. Enhancing the CH selection step is crucial as it is one of the crucial stages of wireless communication. The significant increase in WSNs' overall achievement is reflected by this advancement. In this paper, author examine many significant cluster formation and selecting CH approaches, including A-LEACH, MWCSGA, DEEC-Gauss, and eeTMFO/GA. The research yields important findings that may be used to choose the optimal algorithm for CH selection, including energy consumption, reliability, the number of nodes that are still alive, longevity, and network throughput.

Sharma *et al.* [23] explained the field of energy-efficient steered computations within remote sensor systems (WSNs) for precision in agricultural businesses. Key metrics including lifespan, energy usage, and information transmission rate were taken into consideration when evaluating four prominent techniques: LEACH, EEUC, PSO-based steering, and ACO-based routing. Authors study adapts to trends in utilizing bio-inspired optimization and machine learning incorporation to tackle the intriguing problems presented by dynamic agricultural scenarios in contrast to earlier work. The outcomes show that EEUC effectively advances vitality adjustment by distance-based clustering, promoting a 25% increase in organized lifespan in comparison to filter. When compared to sorting, PSO-based routing and ACO-based directing show adaptability to varying circumstances, improving organize lifespan by 20% and 18%, respectively. The summarization of the work done on precision based farming using WSN is as shown in Figure 1.

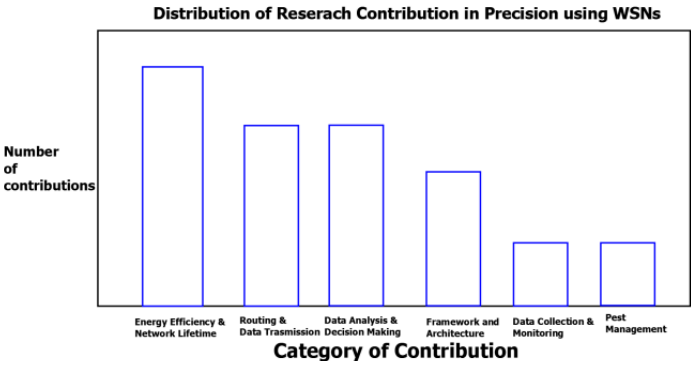

Figure 1. Research contributions in PF using WSNs

The chronological research for the substrate integrated waveguide (SIW) resonator [5]–[7], supported by references [2], [4], began with research design where theoretical parameters (like W_{eq} and L) were calculated based on the target frequency and material properties. This was followed by Research Procedures, which involved an iterative process of computer-aided design (CAD) modeling and electromagnetic (EM) simulation, guided by a design algorithm, to optimize the physical dimensions and achieve target performance metrics [8]–[11]. Finally, the design entered the data acquisition and testing phase, where the fabricated prototype was tested using a vector network analyzer (VNA) to measure the return loss (S_{11}), and insertion loss [12], [13], along with the results presented scientifically validate the simulation model [2], [4]. The Table 1 shows the work carried out on PF using WSN. The components used in different proposed work along with their motivation have been listed here.

Table 1. PF techniques along with components used for sensing the various parameters and also their supervising methods

Ref.	Description	Components used	Supervising	Advantages	Disadvantages
[24]	In cultivated fields, a measuring system was created to track soil moisture levels as well as air, soil, and canopy temperatures.	The microcontroller based system and solid-state sensors.	Surveillance on cultivated fields' canopy, soil, and air temperatures as well as their soil moisture content.	Good accuracy for the cost, portable and ease of assembly.	Reliability issues, limited connectivity, lack of a user-friendly interface.
[25]	A WSN-based irrigation system for farmers.	Soil node, weather node, and container node.	Weather node measures environmental factors including air temperature, humidity, wind speed, and brightness, the soil node will detect soil temperature and moisture.	Cost-Effectiveness, real-time monitoring and remote access.	Scalability concerns, potential for single point of failure.
[26]	ZigBee-based wireless solution for an intelligent field irrigation system used for Jew's ear planting in Lishui, Zhejiang, China.	A weather station, many wireless actuators, and a sensor node.	While the adjacent weather station tracks the meteorological data, indicating whether it will rain, the sensor node gathers the temperature and air humidity measurements in its area.	Low power consumption, scalable network architecture	Limited range and data rate, susceptibility to interference
[27]	Creating an intelligent, low-cost irrigation system using IoT.	Soil moisture sensor, temperature, humidity sensor and controller.	Provides real-time agricultural information by monitoring crop water requirements and notifying the user and irrigation unit of them. Monitors water use using a plant watering system that operates automatically.	Cost-effectiveness, remote monitoring and control	Scalability concerns, network reliability, and security
[28]	Integrating advanced tech can lead to higher productivity, better resource management, and a more sustainable food future in the face of growing global demand and dwindling resources.	Soil moisture, temperature	Technology is used to supervise and control agricultural operations	Boost agricultural resilience, improve resource allocation, and improve food security	Resource optimization, scalability, and security

3. PROPOSED WORK

To enhance agricultural productivity and address global food security, it is crucial to equip farmers with data-driven insights for efficient resource management. A significant challenge, particularly in emerging nations, is the suboptimal use of resources like water, where over-application can lead to decreased soil fertility and wasted energy. Precision agriculture emerges as a critical solution, employing modern technologies to maximize crop yields while minimizing environmental impact.

A key element of this method involves WSNs: arrays of sensors deployed over a space to continuously track environmental factors such as temperature, soil moisture, and nutrient content. The structural layout and interaction of these components within the field are illustrated in the system environment depicted in Figure 2.

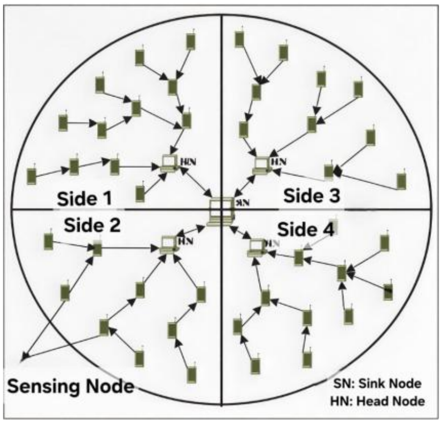

Figure 2. System environment

Figure 2 illustrates the hierarchical arrangement of the sensor network, highlighting the communication pathways between localized node groups and the central gateway. This environment serves as the operational backbone, ensuring that raw data harvested from the soil is seamlessly transitioned through various network layers for real-time analysis and decision-making.

While WSNs are transformative, their widespread adoption is hindered by a major operational challenge: high energy consumption. The continuous operation of numerous sensor nodes across large agricultural fields requires substantial power, making energy efficiency a primary concern.

The major contribution of this research is to address this energy management issue directly. The study focuses on identifying the key factors that influence energy consumption in WSNs within a precision agriculture context. Specifically, it investigates the use of node clustering—grouping sensor nodes into clusters—as a primary strategy to manage and reduce the network's overall energy usage, thereby making precision agriculture more sustainable and accessible.

To prolong the operational life of a WSN, a hierarchical clustering approach is employed where decisions are guided by a precise energy model. This model quantifies the energy cost for transmitting a k-bit message over a distance d as ETx(k,d)=(Ecircuit×k)+(ϵtx−amp×k×dn) and for receiving it as ERx (k)=Ecircuit×k. Using this framework, the network elects a CH based on a two-part criterion [29]: the node must be within direct communication range of the BS, or d(Ni,BS)≤Rmax, and it must possess a residual energy, Eresidual, above a predefined threshold, Ethreshold. The optimal CH is then designated as the eligible node with the highest energy reserve, calculated as CHactive=argmaxNiƐScandidate(Eresidual(Ni)). Furthermore, to maximize efficiency, the active CH uses a temporal redundancy filter, transmitting its aggregated data packet Dt only if it shows a significant change from the previously sent packet Dt−1. This decision, modeled as transmitting only when a difference metric Δ(Dt,Dt−1) exceeds a sensitivity threshold τ, prevents the needless expenditure of energy on redundant information and is crucial for sustainable network operation. The following is the algorithm for CH selection.

One of the data-saving techniques for resource management in WSN is informationaggregation. Several copies of identical information or redundant information may be sent by the sensor. This type of information takes up more space and affects the system's overall efficiency if it is stored. As a result, an information examine is being performed in this instance to ensure that the node is free of duplicate information. Before the information is stored in the sensor node, a methodology is used. This method eliminates unnecessary information from the node database and only keeps the information that is necessary. Minimum, maximum, summation, average, and fusion are the methods used for information aggregation [30].

```
Steps for Selecting CH
Step 1: Initialize the set of candidate nodes
Step 2: Identify all eligible candidates
FOR EACH node N_i in N DO
        distance_to_BS ← Calculate_Distance(N_i, BS)
        residual_energy ← Get_Residual_Energy(N_i)
        IF (distance_to_BS ≤ R_max) AND (residual_energy>E_threshold) THEN
        Add N_i to S_candidate
        END IF
END FOR
Step 3: Select the optimal CH from the candidates
        IF S_candidate is NOT empty THEN
        Designate the CH as the candidate with the highest residual energy
        CH_active ← argmax_{N_i∈S_candidate} (Get_Residual_Energy(N_i))
         ELSE
        CH_active ← null
END IF
Step 4: Return the result
RETURN CH_active
```

Rather of storing both sensory information at the HN, if sensors 1 and 2 provide temperature readings of 40 °C and 42 °C, accordingly. To remove duplicate information and save only one information which incorporates both of the information in the HN database, the information aggregation approach is used. This approach accounts for sensor reliability by assigning a weight (w) to each reading. A more reliable sensor gets a higher weight.

– Equation: $\bar{x}w=w1\times1+w2\times2$, where $w1+w2=1$.
– Example: if sensor 2 (42 °C) is more reliable, we can assign it a 70% weight ($w2=0.7$) and sensor 1 a 30% weight ($w1=0.3$).
  $\bar{x}w=(0.3\times40)+(0.7\times42)=12+29.4=41.4$ °C

This result is more accurate as it is influenced more by the trustworthy sensor.

WSNs are integral to modern PF, creating a data-driven framework to optimize resource management. This system architecture, comparable to those in industrial automation, comprises field sensors, gateways, and a central control unit that executes a workflow of sensing critical parameters, transmitting data, making decisions, and actuating responses like irrigation or fertilization. A defining feature of PF is its reliance on highly customized software models tailored to specific site conditions, including soil type and crop variety, to ensure the precise application of inputs. This creates a critical operational challenge: balancing the need for actionable data with the significant power consumption and network traffic generated by frequent sensing. Therefore, the system must be intelligently optimized to collect data only when it provides new value, preventing network overload from redundant information.

The proposed precision agriculture framework utilizes a comprehensive sensor suite to monitor key environmental and soil parameters, including temperature, humidity, barometric pressure, CO_2 levels, moisture content, and soil pH. This real-time data is integrated into simulation software, establishing a closed-loop feedback system that determines the optimal application rates for agricultural inputs at specific locations and times. The system's control network actively manages functions such as water pressure, irrigation valve operation, fertilizer and pesticide distribution, and even wildlife supervision. Driven by the declining costs of sensor and communication technologies, WSN adoption is expanding beyond traditional agriculture to smaller-scale operations like urban and micro-farms. In these contexts, where space is often at a premium—utilizing vertical trellises on rooftops or adjacent to buildings—maximizing crop yield is paramount, making the efficiency gains from such technology critically important.

Frame format to be used by sensor node to send data from sensor node to head node as as shown in Figure 3. The parameters like temperature, humidity and moisture are considered which gives the status of the soil as well as environmental condition. The frame consists of send prefix along with from which node the data being released. It also consists of date and time of data send from node. The temperature, humidity and moisture havemost significant byte (MSB) and least significant byte (LSB) data which are sent to HN where comparison will be carried with the existing data utilizing resource management technique. The outcome of the resource management explains whether to accept the data or not hence energy will be saved by avoiding further data transmission to the SN. Whenever there is updated data and if the resource management has different value than its previous record then such information will be prioritized and based on the priority the data will be shared with SN.

Start	Identifier	Date/Time						Temp		Humidity		Moisture	
Send	Node ID	DD	MM	YY	ss	mm	hh	MSB	LSB	MSB	LSB	MSB	LSB

Figure 3. Frame format

Algorithms for proposed work and resource management in WSN for PF are presented in Algorithms 1 and 2.

Algorithm 1: nomenclature- N: set of sensor nodes {n1, n2, …, nN}, S: sink node, A: area of deployment, T: time duration for each cycle, E_initial: initial energy of each node, D: set of data collected at the Sink Node, C: set of clusters {c1, c2, …, cM, HN: set of head node {hn1, hn2, …, hnM}, ID(ni): unique ID of node ni, E(ni): current energy of node ni, data(ni): data sensed by node ni, data_agg(ci): aggregated data in cluster ci, data_validated(ci): validated data from cluster ci, threshold: threshold for data transmission, cycle_start_time: time when the current cycle started.

Algorithm 2: the proposed resource management approach operates according to the following steps: nomenclature: data_current(n): current data from sensor node n, data_previous(n): previous data from sensor node n (or baseline), threshold: threshold for data filtering, priority_rules: rules for assigning priorities, data_to_transmit: data to be transmitted to the SN, delta(n): difference between current and previous data for node n, and data_to_transmit = {}.

Algorithm 1. The proposed work

```
1. Network deployment: nodes are deployed in area A
2. Node initialization
for each ni in N do
ID(ni) <- Generate_Unique_ID()
 E(ni) <- E_initial
end for
3. Network setup: nodes establish connectivity and discover neighbors
4. Clustering
C <- Clustering_Algorithm(N, A)
    800 Head Node Selection
for each ci in C do
   p <- Random(0, 1)
    if p < (desired percentage of HN nodes) then
        CH(ci) <- ni where ni is a node in ci with the highest remaining energy and close
to SN
    end if
end for
D <- {}
while True do
    cycle_start_time <- Current_Time()
5. Data Sensing
    for each ni in N do
        if ni is not a CH then
            data(ni) <- Sense_Data()
        end if
    end for
6. Data Processing (Research Management)
    for each ci in C do
        data_agg(ci) <- Aggregate_Data(data(ni) for all ni in ci and ni is not CH(ci))
    end for
7. Data Validation
    for each ci in C do
        if |data_agg(ci)| > threshold then
            data_validated(ci) <- data_agg(ci)
        else
            data_validated(ci) <- null
        end if
    end for
8. Data Transmission
    for each ci in C do
        if data_validated(ci) != null then
            Transmit(data_validated(ci), CH(ci))
        end if
    end for
    for each chi in CH do
        Transmit(data_validated(ci), S)
        D <- D U data_validated(ci)
    end for
```

```
9. CH Rotation
    while Current_Time() < cycle_start_time + T do
      end while
    for each ci in C do
        E(CH(ci)) <- E(CH(ci)) - Energy_Consumed_CH()
        p <- Random(0, 1)
        if p < (desired percentage of CH nodes) then
            CH(ci) <- ni where ni is a node in ci with the highest remaining energy and
near to SN
        end if
    end for
end while
10. End Algorithm
```

This approach makes it possible for the proposed WSN system to gather, analyze, and transmit data efficiently.

Algorithm 2. Resource management in WSN for PF

```
1. Network deployment
2. Data collection (implicit - already received)
3. Data comparison (change detection)
for each sensor node n:
    delta(n) = data_current(n) - data_previous(n)
4. Data Filtering (Thresholding)
relevant_data = {}
for each sensor node n:
    if |delta(n)| > threshold:
        relevant_data[n] = data_current(n)
5. Data Prioritization
high_priority_data = {}
medium_priority_data = {}
low_priority_data = {}
for n in relevant_data:
    priority = Apply_Priority_Rules(delta(n), priority_rules) // Function to determine
priority
    if priority == "high": high_priority_data[n] = relevant_data[n]
    elif priority == "medium": medium_priority_data[n] = relevant_data[n]
    elif priority == "low": low_priority_data[n] = relevant_data[n]
6. Data Transmission (Prioritized)
for n in high_priority_data: Transmit(high_priority_data[n], SN); data_to_transmit[n] =
high_priority_data[n]
for n in medium_priority_data: Transmit(medium_priority_data[n], SN); data_to_transmit[n] =
medium_priority_data[n]
for n in low_priority_data: Transmit(low_priority_data[n], SN); data_to_transmit[n] =
low_priority_data[n]
7. Data Neglect (No Transmission - implicit)
8. Update Baseline (Example: Update with current data)
for each sensor node n:
  data_previous(n) = data_current(n)
9. Repeat Procedure (Handled by outer loop in the main proposed algorithm)
return data_to_transmit
10. End Algorithm
```

This optimized resource management strategy optimizes network resources, reduces energy consumption, and permits effective data gathering, filtering, and transmission. An advantage of resource management in WSN includes; i) energy efficiency: task rotation, information compression, and node clustering all contribute to optimal energy use, ii) improved crop care: effective measures are made possible by real-time tracking of crop health indices, and iii) expanded network lifetime: the network lifetime is prolonged by effective resource management.

4. RESULT AND DISCUSSION

The results of the proposed methodology are outlined below. Performance was judged based on four evaluation metrics: energy consumption, lifetime, delivery ratio, and throughput. The simulation environment's settings are provided in Table 2.

Energy consumption: as the network's cumulative energy use, which is calculated by integrating the energy cost incurred by every node for packet transmission. The governing formula for this calculation is presented as (1):

$$Energy\ Consumption = \frac{Energy\ consumed\ by\ each\ node\ for\ transmission}{Total\ Energy\ Consumed\ by\ the\ entire\ network} \tag{1}$$

Table 2. Simulation parameters

Parameter	Value
Number of sensor nodes	100
Node type	Static
Area of deployment	500 m × 500 m
Initial energy per node	2 J
Transmission range	40 m
Communication protocols	Zigbee
Simulation time	800 seconds
Antenna type	Omni directional
Link	Wireless
Radio type	IEEE 802.15.4

The proposed strategy's energy use was assessed and contrasted with that of a traditional WSN approaches that is LEACH-WSN [31] and Neuro-WSN [32] which had an equivalent number of sensor nodes. The adaptive clustering method, which optimizes sensor node activation and transmission frequency depending on real-time environmental circumstances, is responsible for the suggested framework's considerable energy consumption reduction, according to the investigation. Figure 4 shows that, on average, the suggested structure uses 36% less energy than the traditional framework. This decrease is explained by the dynamic selectionof cluster heads based on proximity and residual power measures, which reduces pointless transmissions and increases the network's overall lifetime.

Network lifetime:one of the most important metrics in WSN applications is network lifespan, which is the amount of time before the first sensor node runs out of energy. When compared to the traditional WSN structure, the suggested design increased network longevity by 44%. The superiority of the suggested architecture in preserving consistent network functionality over long stretches of time is confirmed by the network lifespan study, which is shown in Figure 5.

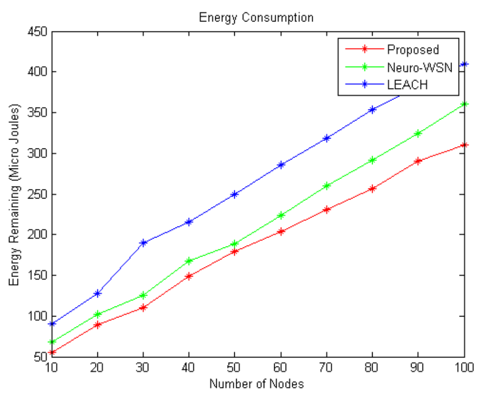

Figure 4. Energy consumption

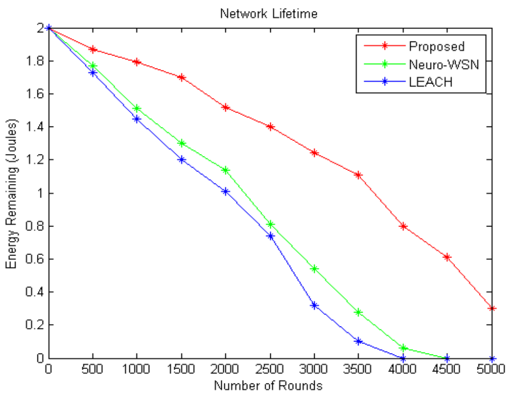

Figure 5. Network lifetime

The lifetime is the amount of time a network can be used to carry out its intended function is referred to as the network's lifetime. The network lifetime is calculated by using (2):

$$Network\ Lifetime\ = \frac{Amount\ of\ time\ taken\ by\ a\ Network}{Total\ Network\ simulation\ Time} \quad (2)$$

Packet delivery ratio (PDR): the effectiveness of the suggested framework's communication was assessed using the PDR. The great dependability of the suggested communication techniques was demonstrated by the PDR, which shows the proportion of correctly delivered packets, which was determined to be 96%. Furthermore, the average latency was lowered to 18 ms, a significant decrease from the traditional framework. Low latency is made possible by fewer hops and efficient routing methods, guaranteeing prompt transmission of vital agricultural information for in-the-moment decision-making. The PDR of the proposed work in comparison with conventional method is depicted in Figure 6.

The PDR as the ratio of packets that are successfully delivered to those that were transmitted, expressed as a percentage. To calculate this key performance indicator, we utilize the formula detailed in (3):

$$Packet\ Delivery\ Ratio = \frac{No.of\ packets\ received\ successfully}{Total\ number\ of\ packets\ transmitted} \times 100 \quad (3)$$

Throughput:the network throughput is the data transmission rate. Its value is determined using the calculation specified in (4). The throughput for the proposed work in comparison with the conventional method is as shown in Figure 7.

$$Throughput \ = \frac{No.of\ successful\ packets \times Average\ Packet\ Size}{Total\ Time\ taken\ for\ delivering\ certain\ amount\ of\ data} \tag{4}$$

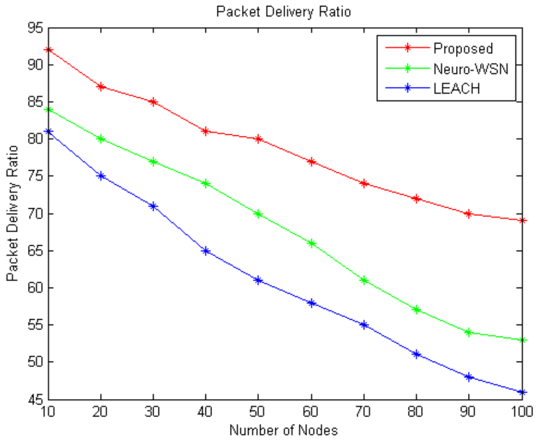

Figure 6. PDR

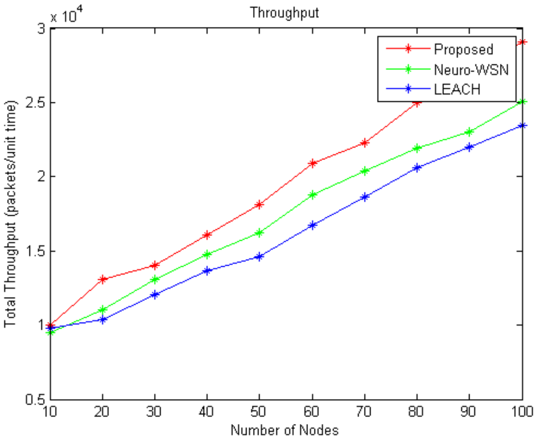

Figure 7. Throughput

In comparison to the current LEACH and Neuro-WSN protocols, the proposed work shows gains in network lifespan, throughput, and PDR. This implies that there may be benefits to the suggested method of resource management in WSNfor PF in terms of energy efficiency, data transmission speed, and communication dependability.

Table 3 clearly shows the advantages of the proposed work across all key metrics. It consumes significantly less power, lasts longer, is more reliable, and transmits data faster than the conventional LEACH and Neuro-WSN methods.

Table 3. Comparison table

Performance parameter	Proposed work	LEACH-WSN andneuro-WSN	Key advantage of proposed work
Energy consumption	Uses 32% less energy	Higher energy consumption	Significant improvement in energy efficiency, leading to longer operational times for individual sensor nodes.
Network lifetime	42% longer lifespan	Shorter lifespan	The overall network remains functional for a considerably longer period, ensuring sustained data collection.
PDR	94%	Lower than 94%	Demonstrates superior reliability in data transmission, ensuring that a very high percentage of data packets reach their destination.
Latency	18 ms	Significantly higher	Low latency allows for rapid data transmission, which is crucial for making timely, in-the-moment decisions.
Throughput	Higher rate of data transfer	Lower rate of data transfer	The network can handle a greater volume of data successfully, indicating more efficient communication.

5. CONCLUSION

This research successfully presents an optimized resource management system that significantly advances PF through the use of a cluster-based WSN. The core achievement of this work is the establishment of a powerful framework that intelligently manages farm resources, such as water, to directly enhance crop yields while simultaneously bolstering the performance of the sensory network. Our findings conclusively show that the proposed methodology leads to marked improvements across critical operational metrics, including a substantially extended network lifetime, higher data throughput, and a significant reduction in overall energy usage. By harmonizing agricultural needs with network efficiency, this study provides a robust and scalable solution that empowers farmers with a reliable, long-lasting, and data-rich tool for superior, sustainable land management.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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