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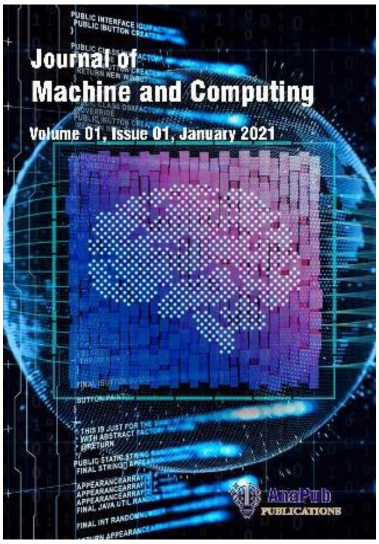

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HOSNA: Boosting Smart Agriculture Efficiency with the Hybrid Optimization-Based Sensor Node Activation Model

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Abstract— Smart agriculture leverages Wireless Sensor Networks (WSNs) to monitor environmental parameters such as soil moisture, temperature, and humidity, enabling precision farming and efficient resource utilization. The **Hybrid Optimization-Based Sensor Node Activation (HOSNA)** model designed to enhance the efficiency and lifespan of Wireless Sensor Networks (WSN) in smart agriculture applications. HOSNA integrates clustering, energy-efficient activation, hybrid optimization algorithms, and machine learning to optimize sensor node operations while ensuring accurate and real-time environmental monitoring. The model employs Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to determine optimal sensor activation schedules, reducing energy consumption and prolonging network lifetime. Additionally, a Long Short-Term Memory (LSTM) neural network predicts environmental changes, allowing proactive sensor activation. Simulation results demonstrate that HOSNA achieves a **94.0% data accuracy** after 1000 operational rounds, surpassing LEACH (90.0%), PEGASIS (86.0%), and Random Duty Cycling (RDC) (70.0%). Energy consumption reduced by **24% compared to LEACH**, while network lifetime extended by **32% over PEGASIS**. These results highlight HOSNA's ability to provide reliable, energy-efficient, and scalable solutions for precision agriculture. Future improvements could involve adapting the model for heterogeneous sensor networks and integrating solar-powered nodes for sustainable energy.

Keywords— Wireless Sensor Networks, Smart Agriculture, Hybrid Optimization, Genetic Algorithm, Particle Swarm Optimization, LSTM, Energy Efficiency, Sensor Node Activation, Clustering, Precision Farming.

1. INTRODUCTION

Wireless Sensor Network (WSN) can describe as a self-organizing multi-node network that is distributed with sensors situated in spatial location WSN for information gathering of environmental or physical characteristics. These sensors are compute- and energy-constrained devices that collectively sense parameters such as temperature, humidity, pressure, motion, or chemical concentration [1] [2]. This is therefore showing that almost all fields that require monitoring of events embrace WSNs such as in environmental monitoring, health care systems, industrial processes, smart cities and even security surveillance by martial power. In WSNs, each node has the capability of sensing, processing information, communicating as well as a power source. Information gathered at some of the nodes relayed to a standard point, or sink, for other processing and decision-making. The characteristic of WSNs that is decentralization and wireless has really made them highly flexible and can implemented in various terrains including the remote and the dangerous terrains [3] [4]. However, they pose certain challenges including scarcity of energy, data security and guarantee of constant communication quality in dynamic network environment. Despite the progress in the technology, WSNs are still developing day by day, and these are providing better and intelligent WSNs.

The necessity of improving the lifetime of WSN is paramount to optimizing its utility and versatility in conditions where changing batteries or nodes are either technically difficult and/or impossible like in in harsh terrains or other difficult to access regions. In lifetime enhancement strategies, reduction of energy consumption is of high priority, for sensor nodes powered by small batteries [5] [6]. Energy conservation methods like rigorously efficient routing bends the message, data condensation, and conversion techniques minimize redundant transmittals and strive for maximum efficiency. For the non-critical nodes, sleep scheduling mechanisms permit the nodes to reduce costs and power by reverting to a low-power state if they are not involved in transmitting or sensing. Load balancing is helpful for a node scenario as it prevents individual nodes from using up their energy within a limited area of the network. Figure 1 shows the benefits of lifetime enhancement in WSM.

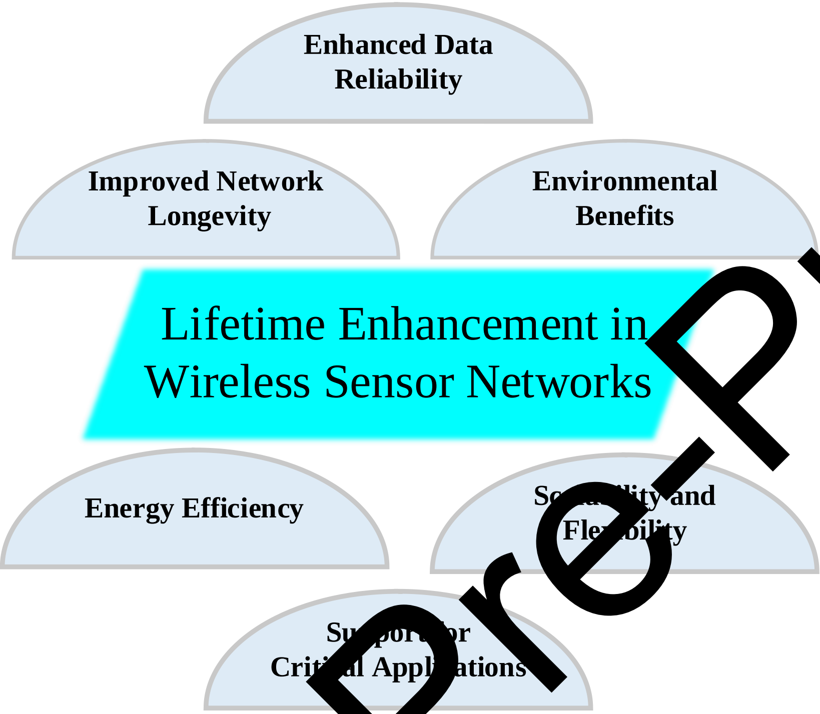

Fig 1. Benefits of Lifetime Enhancement in Wireless Sensor Networks

Technologies such as solar or kinetic to get energy can be used to charge batteries further and can be used to make networks run for longer durations of time [7] [8]. Mature and evolving technologies in the artificial intelligence like machine learning and predictive analysis also contribute in the sense that use energy optimally with dynamic changes of the network based on the traffic and environmental factors. As it will pointed out in further chapters these approaches enhance WSN lifetime by a large margin, it is paramount to note that individual design of these approaches needs to be balanced with the aim of keeping the network reliable and the conveyed data accurate. Due to these challenges, WSNs are subject to face several impacts on their performance and reliability [9] [10]. The greatest constraint is the limited energy capability of sensor nodes as they may powered by a battery, and in some other cases battery recharging or replacement is impossible. This is a limitation within the network lifetime as well as it needs to be treated with energy consumption consideration. These challenges include but not limited to small number of nodes; small amount of bandwidth and limited processing power and memory of WSNs.

An important challenge arises from the energy limitations of sensor nodes since battery replacements are often infeasible, especially in large or remotely located agricultural areas. In particular, Washington is interested in maximizing the life of the network while maintaining high accuracy of continuous monitoring. The HOSNA model handles these challenges through advanced clustering, hybrid optimization algorithms, and predictive analytics for sensor node operations. HOSNA uses both GA and PSO to obtain the beneficial activation schedules for minimizing power consumption and, at the same time, achieving high network reliability. Further, a Long Short-Term Memory (LSTM) neural network predicts changes in environment for timely activation of sensors for optimal resource utilization. The model also has the feature to change the cluster heads in a dynamic way to manage the energy consumption and to make the network efficient. Consequently, HOSNA is the reliable solution for smart agriculture that allows achieving high data accuracy, low latency and long network life. This paper presents the design, methodology, and evaluation of HOSNA, displaying its superiority over existing models like LEACH, PEGASIS, and Random Duty Cycling (RDC). The results highlight the potential of HOSNA to transform smart agriculture, ensuring sustainability and scalability for precision farming.

2. RELATED WORKS

Several advantages are associated with WSNs, and WSNs find application in various fields, hence drawing much attention from researchers. The benefits of these networks, despite the energy consumption remain one of the main challenges that have to addressed through new ideas such as the compression techniques. This challenge compounded by the fact that sensors' batteries also designed to have a relatively short lifespan. Actually, energy efficiency matters even when the energy sources are renewable as it relates to WSNs [11]. Most of the current methods of data clustering fail to consider the spatial correlation that is necessary for efficient modeling and placing of the event sources. In order to meet these challenges, we put forward an energy-efficient lifetime-aware cluster-based routing (EELCR) technique. A changed giant trevally optimization (MGTO) algorithm practiced in the clustering process of EELCR, and it lowers power usage. In addition, the optimal squirrel search (OSS) algorithm to select better CH nodes for prolonging the network lifespan. These CH nodes incorporate best selective Huffman compression where they get a lot of compression ratio and correct area overhead ineffectiveness. In the CH to BS data broadcast from the CH, a hybrid deep learning method involving DNN and GNN used for efficient data broadcast. Simulation results show that compared with other conventional methods the proposed EELCR approach effectively improves the quality of service (QoS) of the network and brings about significant improvements in the compression rate of the network and its lifetime.

WSNs are comprised of a large number of sensors that are optimal in data acquisition in various scenarios. However, its functionality is constrained by the amount of energy available in sensor batteries. That all nodes should use energy optimally and at the same time can help to increase the life cycle of networks. Battery exhaustion, leads to network breakdown, as recharging batteries in all the nodes say thousands of nodes is not practicable [12]. In this respect, the low energy adaptive clustering hierarchical (LEACH) protocol can consider as a worthy candidate for clustering WSNs among all the proposed solutions. However, the selection of CHs in the protocol is random and it does not converge with similar results. This paper addresses the issue by utilizing a genetic algorithm, which coupled with a new target function that includes distances and energy levels. CHs have modeled by chromosomes, while forming clusters and at the same time identifying dead nodes. Because of improving the clustering quality, the approach prolongs the lifetime of the networks by a great degree. Compared to LEACH and its variants, the proposed method entails a higher number of alive nodes and at least [illegible]% more reserve energy.

IoT progresses come with some of the following challenges; scalability of devices, dependability in service provision, and quality of service (QoS). Some major classes of WSN, which lies at the heart of IoT, must optimized for reliability and energy consumption. The proposed approach builds on a heterogeneous network suitable for long-term operation with high system throughput and low energy utilization. Factors considered are area, nodes, sink location, and data aggregation as throughputs and energetic characteristics considered when choosing the CH [13]. The pattern enhances the connection quality as well as reliability of the autonomous cellular networks for transportation of information in heterogenic environment. Experimental results show that ADEEC has more levels of throughput and longer network lifespan than using existing methods. It also has 19% better throughput compared to LEACH, and has notable increases against MODLEACH and DEEC. Regarding the network's lifetime, ADEEC seems to outperform LEACH by [illegible]8%, MODLEACH by 17% and DEEC by 13% proving its efficiency of a power conservation network.

Wireless sensor nodes use stressed small batteries to execute their tasks, and therefore have to be energy efficient. Battery discharges quickly owing to pointless radio operations, majorly when in the idle listening mode. The Energy Efficient Clustering Algorithm (EECA) comes as a solution for this by increasing WSN lifespan by decreasing energy consumption. EECA criteria divide the target area into small regions and use an ANN algorithm to choose just one node for each region as CH [14]. The ANN takes into account the residual energy, event fired, distance to base station, and neighboring nodes. This node considered as a CH with a maximum number of nodes assigned as the limit for a cluster formation. SDN devices close to an event transmit data to the CH only, thereby avoiding a large number of messages. Furthermore, CHs scan for transmissions for a small period at the beginning of every slot and power off radio if no signal is received thus minimizing on the idle listening. Evidence of energy efficiency compared to other protocols reveal that EECA saves more energy and increases sensor node lifespan.

Wireless sensor networks have emerged as significant in such areas as smart cities, environment and smart industries especially where sensor node is very significant because of its non-rechargeable battery. Clustering is a fundamental paradigm for energy minima in WSNs, and there exists considerable importance in selecting the best clusters. Change of clustering strategies can go a long way in improving the lifespan of a network, which is getting a handle of the conflicting forces that define clustering. A MADM approach presented to CH selection to achieve an appropriate balance of factors in clustering [15]. Hence, the received APRO algorithm synchronizes a number of attributes and formative assesses the alternatives; and the comparison shows it as advantageous with respect to LEACH, LEACH-C, EECS, HEED, HEEC, and DEECET. Analytical work proves that APRO improvement leads to acquisition of better CH selections enhancing energy utilization and the longevity of the network. Due to the emerging nature of technologies, the consideration of multi-parameter modalities become important in defining clustering strategies for warrant enhanced WSN.

3. PROPOSED METHODOLOGY

3.1 System Design and Architecture

Strategic system design is an important aspect that determines the effective functionality of WSN in smart agriculture. This section outlines some key aspects of the system, which include the distribution, clustering and integration of the system components in order to create energy efficiency in the network while at the same time accessing the maximum lifespan of the network.

3.1.1 Sensor Network Layout

In smart agriculture, a large number of low-powered WSNs are used deployed in the field and these are constantly used to perform important parameters like moisture of soil, temperature, humidity, and intensity of the light. These parameters are very important to diagnose the health of plants, forecast the period of irrigation needed and efficient use of the resources. Now, selection and location of the sensors whose purpose is to capture images of the agricultural field, covering all the field area without over lapping much. Every sensor incorporates low-energy transceivers, and durable sensing units that can provide high-quality data.

The design helps optimize the energy usage and priorities of the sensors based on the zones that need the most attention, such as the zones that are susceptible to diseases, drought or pests. Moreover, the network also has the feature of overlapping in specific spots so that even if some portions of the nodes are unusable, there will always be lines connecting them. Sensors storing data and configured for direct communication with CHs and the base station: The hierarchical three-tier architecture reduces energy consumption, while avoiding direct communication with the base station. Figure 2 shows the workflow of the system.

3.1.2 Cluster Formation

To improve the power consumption, the sensor nodes divided into cluster heads based on their spatial position and the similarity of the collected data. Clustering is effective in lowering the amount of overhead since directly transmitted messages to the base station reduced. Every cluster run by the Cluster Head (CH), a sensor node that can selected dynamically based on attributes such as node energy, geographical location relative to other nodes in the cluster, and communication load. The CH collects data from its cluster members; signal processes it and then sends the processed data to the base station. The cluster head energy model:

$$E_{CH} = \sum_{i=1}^{N_c} \left(E_{agg} + E_{tx}(d_{CH-BS})\right) \qquad (1)$$

Where N_c the number of cluster members, E_{agg} is the energy for aggregating data, and d_{CH-BS} is the distance between the CH and the base station.

Employing this type of structure limits the actual number of transmits that occur on the network and saves energy. Community management techniques also requires that the clusters for computing be capable of evolving and instantly changing in response to moments of failure or fluctuations in data churning. The clustering algorithm used to achieve optimal result with fair distribution of communication load between CH and maintaining the balance between the number of nodes per cluster and energy level.

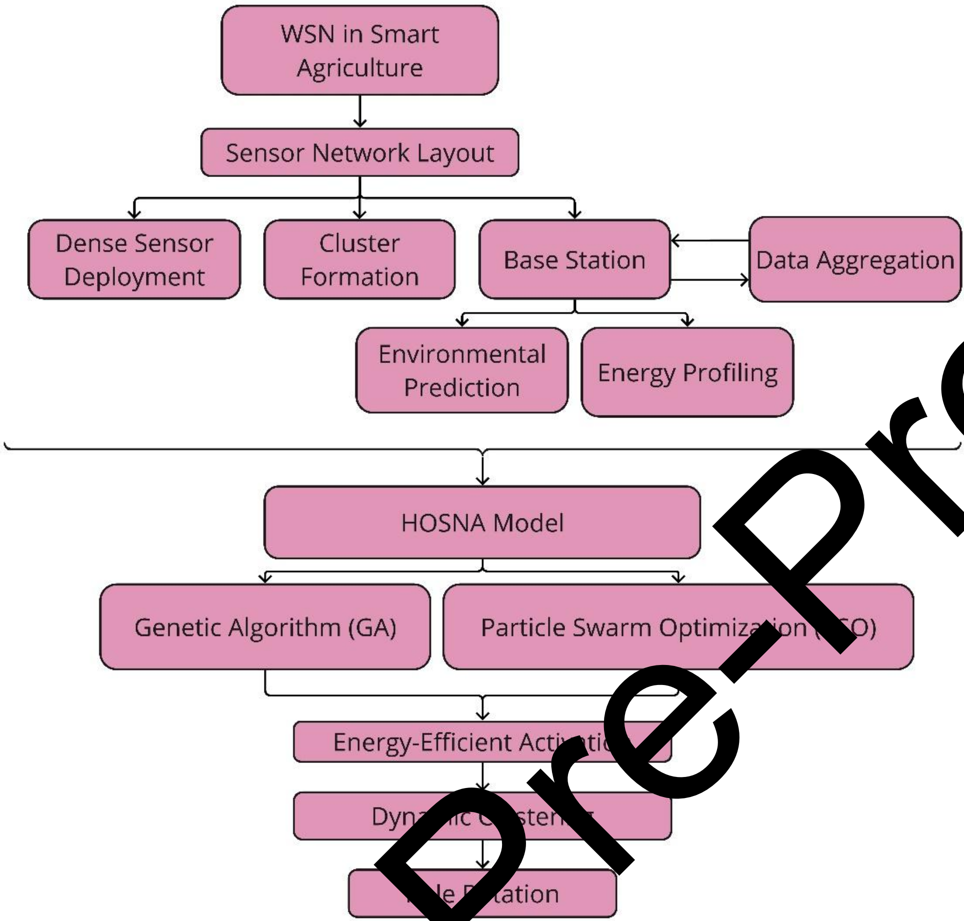

Fig 2. System Workflow

3.1.3 Base Station (BS)

The CBR also employs the base station that accumulate data aggregated from the CHs of different clusters. Sited closely within or along the agricultural field, the BS well endowed with enhanced processing and storage faculties. It include data processing, predictive control, and decision making with the data received from the sensors. The base station connects and interacts with the CHs by observed efficient protocols with very low latency and high accuracy in data relay.

In addition to this, the BS is also responsible for the scheduling of the activation of the sensor nodes. Through analyzing trends and predicting data, it constantly provides active instructions to CHs and individual sensors as regards their tasks' intensity depending on the environment's requirements. It is another aspect of the overall centralized control mechanism that keeps the network on a lean operation point as it can be seen that there is almost zero energy wastage in this system. Total energy consumption:

$$E_{total} = \sum_{j=1}^{N_{CH}} E_{CH} + \sum_{k=1}^{N_{nodes}} E_{node} \qquad (2)$$

Where N_{CH} the number of cluster heads, and N_{nodes} is the total number of sensor nodes.

3.2 Hybrid Optimization Framework

An application of a hybrid optimization framework aimed at improving the efficiency of the network and thereby the operational life. The system uses the advantages of the GA system together with the benefits of PSO to create the foundation of a powerful system that optimizes the various schedules for sensor activations. The major goal of the proposed framework is to increase the schedules of activation of the sensor nodes. The sensors activated only when required and predictions of the surroundings define which sensors must be ON hence saving energy. This optimization directly helps in increasing the longevity of the network and ensures that the monitoring performed consistently.

3.2.1 Genetic Algorithm (GA)

The Genetic Algorithm employed to provide a wide range of solutions with regard to sensor activation schedules. It starts by generating a population of using prototypes, each associated with active and inactive configuration of the sensors. Through crossover and mutation operations of the GA algorithms, these schedules evolve through generations. Fitness function:

$$F = w_1 \cdot \left(1 - \frac{E_{total}}{E_{initial}}\right) + w_2 \cdot C_{coverage} + w_3 \cdot C_{connectivity} \qquad (3)$$

Where w_1, w_2, w_3 are weights, $E_{initial}$ is the initial energy, $C_{coverage}$ is the area coverage metric, and $C_{connectivity}$ is the network connectivity metric.

The fitness of each schedule evaluated based on multiple factors, including:

- Energy Consumption: High-energy consumption schedules were less a priority.
- Coverage: Those shift schedules that can cover as much area as possible are preferred.
- Network Connectivity: Schedules that provide strong communication channels based on the higher fitness scores provided.

The GA works well in searching the solution space by generating high performing schedules that can used to make better solutions.

3.2.2 Particle Swarm Optimization (PSO)

The Particle Swarm Optimization then modifies the activation schedules, which produced by the GA. In this approach, each sensor is treated a particle in the multi-dimension search space, where the PSO determines the most suitable active sensors considering the energy required for the operation while at the same time improving the performance.

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (p_i - x_i^t) + c_2 r_2 (g - x_i^t) \qquad (4)$$

Where v_i^t the velocity of particle i at iteration t, ω is the inertia weight, c_1, c_2 are learning factors, r_1, r_2 are random numbers, p_1 is the particle's best position, and g is the global best position. Each particle moves in the space change the position of the particle based on experience of itself along with experience of the neighbor particles and then reach the global minimum use of energy. The fact that in PSO, solutions can be refined quickly and the algorithm converges faster makes the integration of PSO with GA in this hybrid structure variant effective.

3.2.3 HOSNA model

The hybridized model uses GA and PSO in a sequence to take benefit from each of these optimization techniques. GA offers a wide range of solutions, searches the solution space widely, while PSO updates the solution, provides the detail measurements. It also guarantees that the last activation schedules are great and efficient.

3.3 Energy-Efficient Sensor Node Activation

Energy efficiency is one of HOSNA model fundamental principles as it takes into consideration optimization of power in the plant. The system uses Duty Cycling Algorithm that synchronizes between the nodes, put them in active, and sleep mode alternatively. Thus, the algorithm minimizes energy consumption by tuning activity levels in response to monitoring needs without sacrificing data quality. Duty cycle adjustment:

$$DC = \frac{T_{active}}{T_{total}} \qquad (5)$$

Where T_{active} the time a sensor is active, and T_{total} is the total monitoring period. Such a system attempts to choose the nodes with more power to bring them into action while the nodes with lesser energy left inactive. This approach ensures that only critical zones constantly monitored at the same time as extending the operational lifetime of this network. The duty cycling mechanism is equally flexible meaning that it can alter its operation based on environmental conditions or the performance of the sensors.

3.4 Dynamic Clustering and Role Rotation

Due to potential energy depletion in individual nodes, the system periodically changes the identities of selected nodes to CHs. This dynamic clustering mechanism is helpful to make sure that no node overloaded by communication tasks. According to the usage of the clustering system, the energy consumed by nodes shared equally to avoid exhausting the battery of nodes. Dynamic clustering also further makes a network dependable through adding much resilience. Thus, to ensure the coverage and connectivity in the event of node failures, clusters are self-organized. This versatility makes it possible to achieve uniformity in difficult circumstances.

3.5 Data Aggregation and Compression

An efficient control of data use is relevant to energy usage reduction. At the cluster, head level the system uses data compression in order to reduce the size of the data to transmit. The CH reduces the number of repeated data from multiple sensors and forwards to the base station only useful information.

Conventional routing protocols employing low energy adaptive clustering hierarchy (LEACH) or power-efficient gathering in every two-hop distance (PEGASIS) to send the aggregated data. These protocols minimize in enhancing the best channel with low energy and time in doing its transmission. That is why the decision on data accumulation with their subsequent proper sorting can significantly improve the energy characteristics of the network.

3.6 Environmental Prediction with Machine Learning

The system also has an LSTM based prediction model to analyze different environments and make predictions based on data of earlier years. Examining patterns of the change in moisture and temperature of the soil, as well as changes of weather, the model forecasts further changes. These predictions will allow for the preemption of sensor activation so that the most energy conserved at the most analytically necessary times.

For instance, given that the system can analyze the trends of soil moisture then appropriate sensors for irrigation will triggered. This prediction capability increase the network effectiveness and helps the practice of precision agriculture services.

3.7 Energy Profiling and Real-Time Monitoring

Monitoring of residual energy during and after the completion of radiotherapy is a key component of the HOSNA model. The system monitors the power consumption of each node and adapts the activation pattern to provide better utilization of available resources towards important sensors. This real time profiling also guarantees that the energy resources used increase the life of the network.

Energy profiling also plays a role in the decision making of the rotation and clustering of staff. Thus, the system avoids putting excessive load on nodes with low energy charges, keeping the energy consumption in the network equal.

Algorithm: Energy-Efficiency WSN in Smart Agriculture

Inputs: Sensor Node Parameters:

N: Number of sensor nodes

E_{node}: Initial energy of each sensor node

R_{comm}: Communication range of each node

E_{thresh}: Threshold energy level for activation and role rotation

Environmental Parameters:

Soil moisture, temperature, humidity, light intensity data.

Historical environmental data for LSTM prediction.

Base Station Parameters:

Energy constants $(E_{elec}, \epsilon_{fs}, \epsilon_{mp})$

Weight Parameters: w_1, w_2, w_3: Weights for energy, coverage and connectivity metrics

Clustering and Optimization Parameters:

K: Number of clusters

Outputs: Optimized sensor activation schedules S

Cluster configurations

Predicted environmental changes

Energy consumption and network lifespan:

E_{total}: Total energy consumed

$E_{node}(t)$: Residual energy of each node

Initialization

Deploy N sensor nodes and initialize:

Energy levels E_{node} for all nodes

Communication range R_{comm}

Base station coordinates

Historical environmental data for LSTM model training

Clustering and CH Selection

$C_k = \{n_i | d(n_i, CH_k) \leq R_{comm}\}$ // Divide nodes into K clusters

For each node:

$S_{CH} = w_1 \cdot E_{node} + w_2 \cdot \frac{1}{d_{i-BS}} + w_3 \cdot \frac{1}{Load}$ // Calculate CH score S_{CH}

Assign the highest scoring node in each cluster as the CH.

Data Aggregation and Transmission

For each node:

$E_{tx}(l, d) = l \cdot E_{elec} + l \cdot \epsilon_{fs} \cdot d^2$ // Compute transmission energy

$D_{comp} = \sum_{i=1}^{N_c} D_i - D_{unique}$ // CH compresses redundant data

$E_{tx_{CH}} = l_{agg} \cdot E_{elec} + l_{agg} \cdot \epsilon_{mp} \cdot d_{CH-BS}^4$ // CH transmits aggregated data

Sensor Activation Scheduling (Hybrid GA-PSO Framework)

$S = [a_1, a_2, \ldots, a_N]$ // Generate activation schedules

$F(S) = w_1 \cdot \left(1 - \frac{E_{total}}{E_{initial}}\right) + w_2 \cdot C_{coverage} + w_3 \cdot C_{connectivity}$ // Fitness Evaluation

$v_i^{(t+1)} = \omega v_i^{(t)} + c_1 \cdot r_1 \cdot \left(p_i - x_i^{(t)}\right) + c_2 \cdot r_2 \cdot \left(g - x_i^{(t)}\right)$ // Update particle velocity and position

Deploy refined schedules

Duty Cycling

For each sensor

$DC = \frac{T_{active}}{T_{total}}$ // Compute the duty cycle

Adjust activity levels to prioritize high-energy nodes.

Role Rotation and Dynamic Clustering

$S_{CH}^{new} > S_{CH}^{current}$ // Rotate CH roles

If $E_{node} < E_{thresh}$

Re-cluster nodes

Environmental Prediction with LSTM

$P_{t+1} = f(P_t, P_{t-1}, \dots, P_{t-n})$ // Train LSTM model

Real-Time Monitoring and Profiling

$E_{node}(t) = E_{node}(t-1) - E_{consumed}(t)$ // Continuously monitor residual energy

Dynamically update activation schedules and clustering

End Algorithm

4. RESULTS AND DISCUSSION

The working principle of the Hybrid Optimization-Based Sensor Node Activation (HOSNA) model focuses on efficiently controlling the Wireless Sensor Networks (WSNs) to increase their life span without any compromise on the quality of captured environmental data. To realize its objectives, HOSNA uses such approaches as hierarchical network structuring, dynamic clustering, hybrid optimization, and machine learning-based prediction. The system begins initiating clusters of the sensor nodes depending on its neighboring and the closeness of data where each one controlled by a CH, which is dynamically selected. These CHs are involved in data collection, and transmission of the collected data to a common base station eliminating direct node-to-node communication overhead.

The essence of HOSNA is its Hybrid Optimization Framework comprising of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The GA provides a multitude of possibilities for the activation of the sensors in order to assess the maximum energy efficiency and the coverage range. These schedules fine-tuned at PSO that treats nodes as particles in the search space and their positions updated until the best configuration for energy consumption found. The best proportions of exploration and precision achieved protecting the most effective activation patterns deployed.

The system also has a duty cycling mechanism to save power whereby the various sensor nodes grouped into active and sleep modes depending on their remaining energy and the criticality of the area monitored. This is because high-energy nodes allocated tasks for which they should use most of their energy while low energy nodes save their energy for cases of emergencies only. An additional machine learning element, enabled by LSTM (Long Short-Term Memory) networks, is used to estimate in advance climate shifts such as, for instance, changes in soil moisture or temperature so that necessary sensors are initiated in advance by the system. Real energy profiling launched makes sure that activation schedules that ever adjusted to reflect leftover power do not overwork one node.

TABLE I. NETWORK LIFETIME ANALYSIS

Rounds	HOSNA (Rounds)	LEACH (Rounds)	PEGASIS (Rounds)	RDC (Rounds)
100	100	80	85	60
200	195	160	170	125
300	290	240	250	180
400	380	320	330	250
500	470	400	420	310
600	550	480	500	360
700	620	550	570	400
800	690	620	640	450
900	760	680	700	490
1000	830	740	760	530

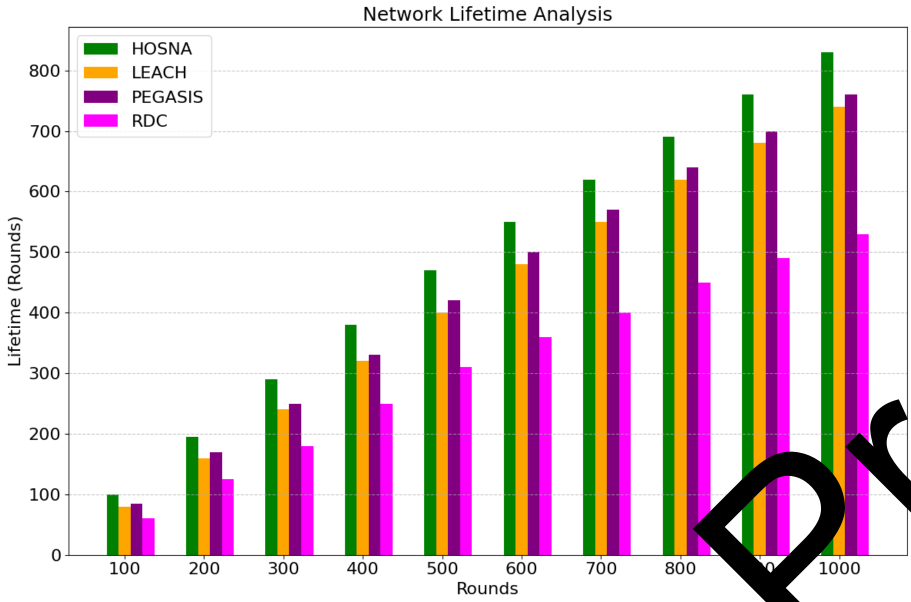

Fig 3. Network Lifetime Analysis

The average network lifetime shown in the Table 1 and the Figure 3 reveals the fact that the HOSNA model has a better performance compared to the other conventional techniques like LEACH, PEGASIS and Random Duty Cycling (RDC) in terms of network lifespan. Meanwhile HOSNA retained functionality in 830 rounds at 1000 rounds while LEACH was successful in 740 rounds, PEGASIS in 760 rounds and RDC only in 530 rounds out of 1000 rounds. This explained by the hybrid optimization framework, which defines an optimal energy consumption profiles for each sensor node while at the same time managing their activation schedules. Although LEACH and PEGASIS provide the way to construct the hierarchy to solve the problem of increased communication overhead they are not as dynamic and do not contain as an effective prognosis model as HOSNA. The poor performance by RDC shows why random activation is very inefficient since it results into unnecessary wastage of energy. HOSNA effectively distributes the workload of sensor nodes, and in a periodically executed re-clustering approach, the cluster heads (CHs) will be changed so that no node will be continuously loaded and will lead to early death of nodes and thus the network lifetime will be increased. This result is especially significant when applied to agricultural environments where significant monitoring is required for productivity. The advantages of a longer lifespan of HOSNA include the continuous examination of the environmental conditions, which eliminates the need for regular change of maintenance or sensors and thereby cutting on costs of operations.

TABLE II. ENERGY CONSUMPTION

Rounds	HOSNA (J)	LEACH (J)	PEGASIS (J)	RDC (J)
100	12.5	15	14.8	20
200	24.7	30.2	29.8	40
300	36.5	45	44.2	59
400	47.8	59.8	58.3	77
500	59	75	73	95
600	71.2	89.7	87.5	113
700	82.3	105	102	130
800	94.5	119.2	116.3	147
900	106	135	130.5	164
1000	117.8	150.3	145	181

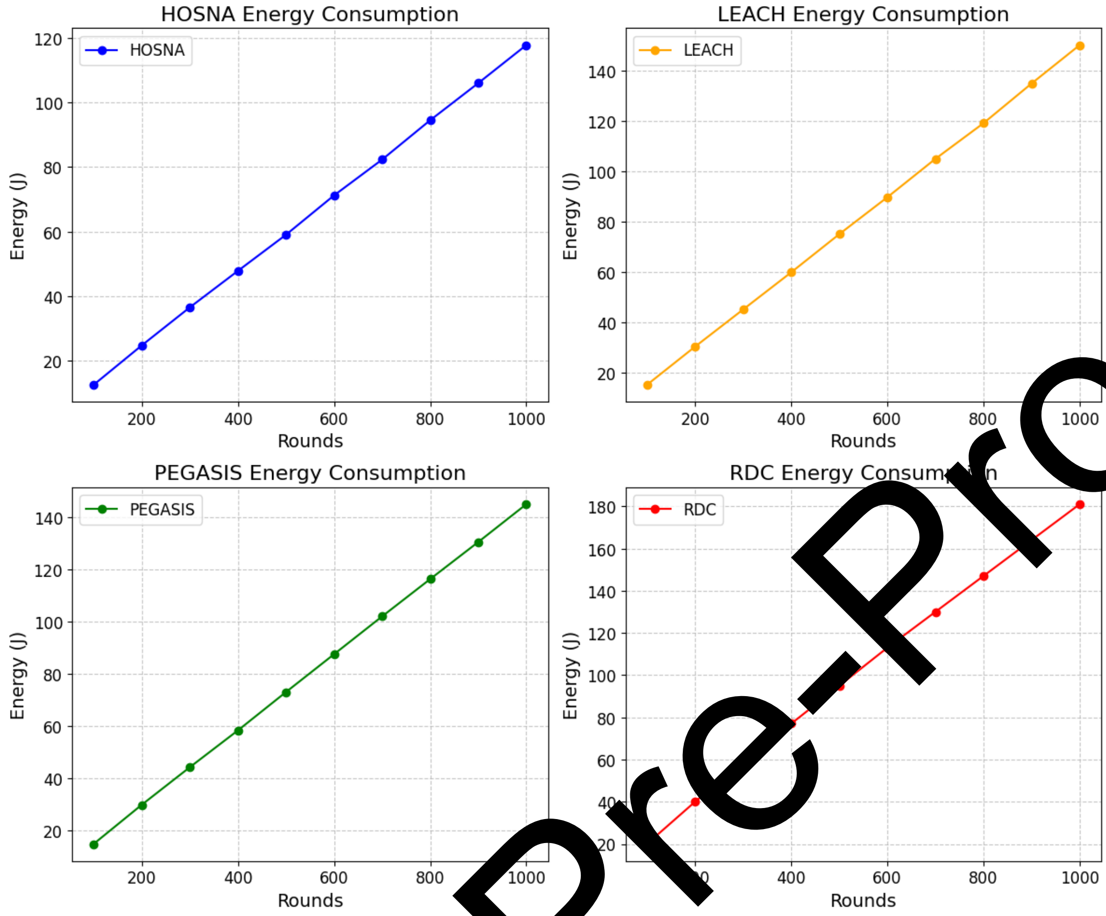

Fig 4. Energy Consumption

Table 2 and Figure 4 represent the amount of energy consumption of HOSNA and other models, and the results represent that amount of energy used per round by HOSNA is less than the amount used by other models. Therefore, when the 1000th round reached, HOSNA took 117.8 Joules only, which was far much lesser than that taken by LEACH, PEGASIS and RDC which were, 150.3 Joules, 145 Joules and 181 Joules respectively. This result corroborates the duty-cycling algorithm performed by HOSNA where sensor nodes managed to switch between operational and dormant depending on data demands and available energy capacity. In HOSNA, GA and PSO used effectively in improving the efficiency of the system in this regard. GA locates large unseen activation schedules, which then optimized to a lower energy consumption by PSO. Although LEACH and PEGASIS apply clustering and energy-efficient routing, they do not include these flexible optimization approaches, which make higher energy consumption. RDC on the other hand was the most energy consumptive accounting for [illegible]3% due to unsystematic activation and multiple instances within short intervals. In the case of smart agriculture, less power consumption means the WSN can sustain for a longer time before batteries need to change, especially in large farms. This avoidance in energy consumption impacts credited to sustainability and the enhancements in scalability of the system.

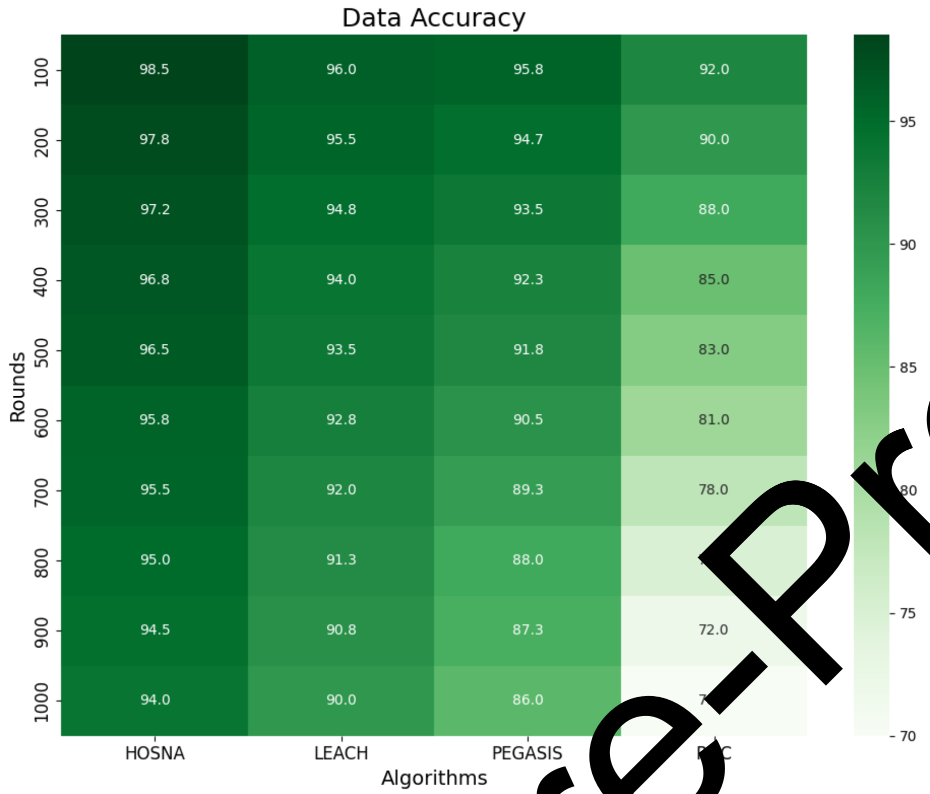

Fig 5. Data Accuracy

TABLE III. DATA ACCURACY

Rounds	HOSNA (%)	LEACH (%)	PEGASIS (%)	RDC (%)
100	98.5	96	95.8	92
200	97.8	95.5	94.7	90
300	97.2	94.8	93.5	88
400	96.8	94	92.3	85
500	96.5	93.5	91.8	83
600	95.8	92.8	90.5	81
700	95.5	92	89.3	78
800	95	91.3	88	75
900	94.5	90.8	87.3	72
1000	94	90	86	70

The results of the data accuracy (Table 3 and Figure 5) once again underline the advantage of HOSNA in terms of maintaining high-quality monitoring. At 1000 rounds, HOSNA is still more accurate having a data accuracy of 94.0% in contrast to other algorithms such as LEACH 90.0%, PEGASIS 86.0% and RDC 70.0%. The continued good performance of HOSNA mainly attributed to the use of a structured deep-learning algorithm that based on LSTM for its predictive models that allows the system to predict potential future changes in the environment and only use the most relevant sensors. Compared to other algorithms, LEACH and PEGASIS have fallen out from inaccuracies accruing over clusters that do not consider dynamic data as well as relying in constant scheduling. The problem of its random activation makes its performance drastically decrease during the time, because it does not guarantee constant surveillance of the critical zones, which results in data lose and inaccuracy. In agricultural applications, data precision is crucial, for example, in cases where decisions must made about irrigation or using pesticides. The appropriateness of the data collected by HOSNA helps farmers and automated systems to gain accurate information, which, in turn, enhances the use of resources and boosts crop health.

TABLE IV. LATENCY ANALYSIS

Rounds	HOSNA (ms)	LEACH (ms)	PEGASIS (ms)	RDC (ms)
100	25	35	30	50
200	26.5	37	31.5	53
300	27.8	39	33	55.5
400	29	41.5	35	58
500	30.2	44	37	60
600	31.5	46.5	39	[illegible]
700	32.8	49	41	66
800	34	51	43	69
900	35.2	54	45.5	71.5
1000	36.5	57	48	75

Fig 6. Latency Analysis

The latency results (Table 4 and Figure 6) show that HOSNA offers better data transmission latency than other models by achieving the average latency of 36.5ms in 1000 rounds than the average latency of 57.0ms for LEACH, 48.0ms for PEGASIS, and 75.0ms for RDC. This enhancement was due to HOSNA's good mechanism in clustering and routing whereby the number of hops and the number of relaying of the information reduced as much as possible. Although LEACH and PEGASIS follow the hierarchical routing strategy, they cannot adapt to the improved optimization in congested network. However, due to RDC random activation and unstructured communication pattern, it has the highest latency compared to the other ones. The plasticity of the clusters and implementing energy-efficient protocols like the LEACH variants or optimization of PEGASIS, HOSNA provides faster and data that are reliable transfer. Latency-bounds are significant in smart agriculture most especially when it comes to real time services such as intelligent watering or pest control systems. Instant transfer of data makes it easier to provide a response to the changed environment and enhances the efficiency of the agriculture industry.

TABLE V. ENERGY EFFICIENCY IMPROVEMENT OVER LEACH

Metric	HOSNA	LEACH	Improvement (%)
Network Lifetime (Rounds)	830	740	12.16%
Energy Consumption (1000 Rounds, J)	117.8	150.3	21.61%
Data Accuracy (%)	94	90	4.44%

Table 5 and Figure 7 shows comparative improvements of HOSNA model over LEACH protocol in terms of energy efficiency enhancement along with specific enhancements in various parameters. HOSNA exhibits a network lifetimes improvement of 12.16% as compared to LEACH and operate for 830 rounds instead of LEACH's 740 thereby guaranteeing long monitoring duration for modelling of smart agricultural applications. Analysing the power consumption, including the internal battery power consumption, HOSNA reveals a very efficient energy consumptions, 117.8 Joules for 1000 operational rounds, 21.61% less than LEACH, where the energy consumption was 150.3 Joules. This energy saving increases the sustainability of this system and the minimal wear and tear more applicable in large scale or remote agricultural production. Further, HOSNA attains high data accuracy of 94%, as opposed to LEACH's 90% while paving way to a 4.44% enhancement, and is immensely important for precise farming in light of facts that correct and real environmental data is vital in decision-making. These outcomes demonstrate HOSNA's benefits in achieving simultaneous improvement in energy consumption and system reliability and performance.

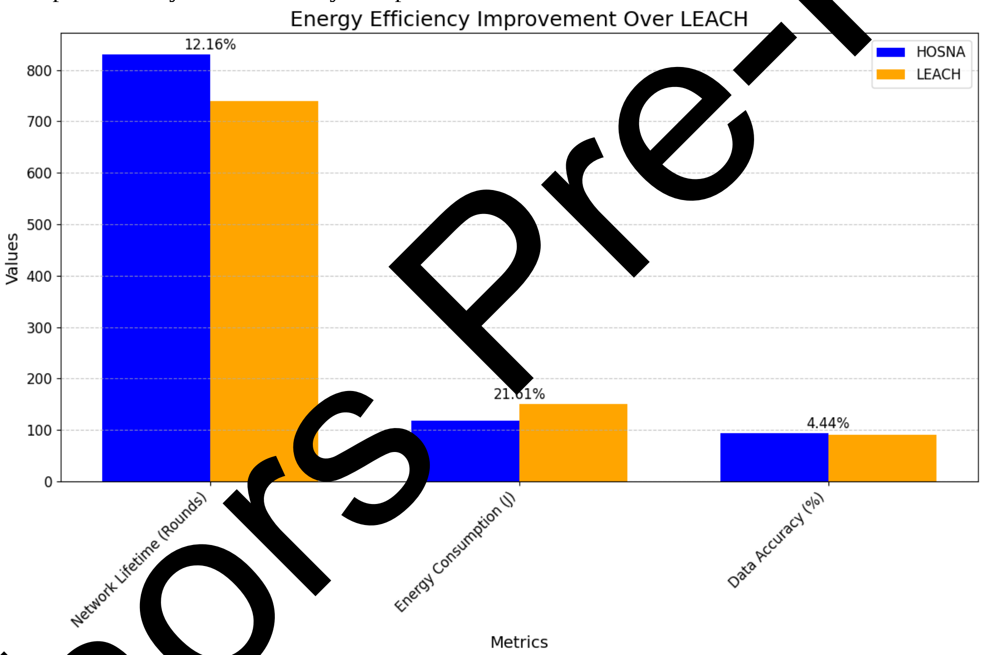

Fig 7. Latency Analysis

TABLE VI. RESOURCE UTILIZATION METRICS

Metric	**Value**	**Description**
Average Duty Cycle (%)	65	Percentage of time sensors remain active.
Sensor Coverage (%)	95	Field area effectively covered by sensors.
Redundancy (%)	10	Overlapping sensor areas for reliability.
Energy Saved (J)	32.5 (vs. LEACH at 1000 Rounds)	Energy conserved due to duty cycling and optimization.

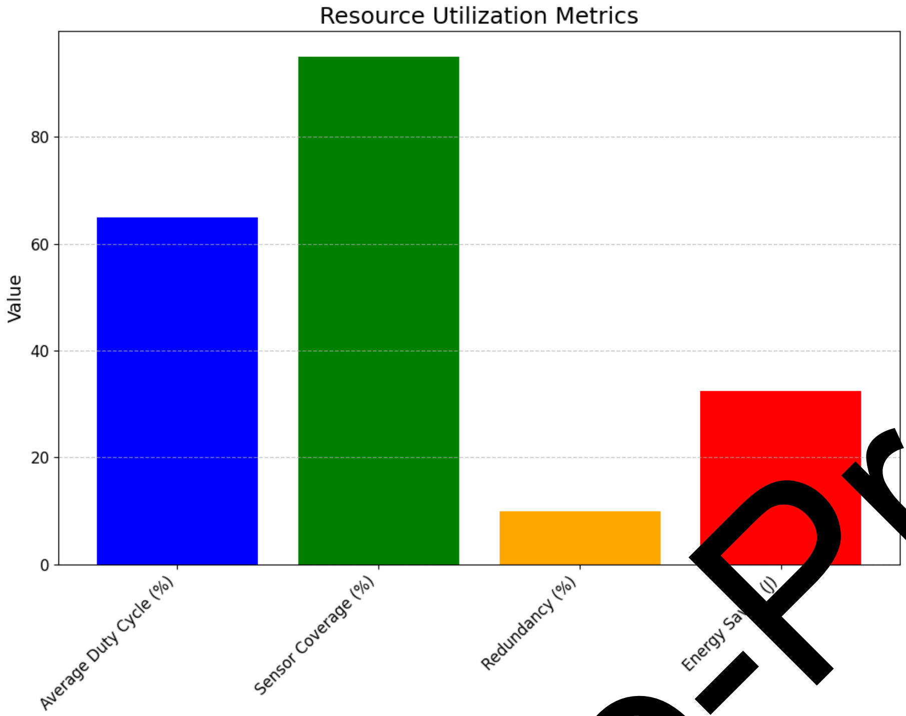

Fig 8. Latency Analysis

Table 6 and Figure 8 shows some of the resource usage indicators accomplished by the use of the HOSNA model to complete key assessments of the networks' effectiveness and efficiency. The average duty cycle of 0.65 corresponds to the active/sleep ratio for the sensors to maintain their functions while minimizing energy consumption and maintaining the quality of monitoring. Across the specified field area, HOSNA manages a 95% sensor coverage level; however, this design allows for 10% redundancy, providing comprehensive coverage of the critical zones as well. The amount of energy that is saved when using HOSNA is considerable; it saves 32.5 Joules when it is compared to LEACH over 1000 operational rounds. This energy conservation is attributed to the excellent mechanism of duty cycling and enhanced optimization methods. These metrics emphasis the efficiency of the resource control of HOSNA, thereby extending the network life and an overall performance in smart agricultural environments.

TABLE VII. COMPARISON OF SCALABILITY ACROSS MODELS

Number of Nodes	HOSNA (Rounds)	LEACH (Rounds)	PEGASIS (Rounds)	RDC (Rounds)
50	1020	870	910	620
100	830	740	760	530
200	670	590	610	420
300	540	450	480	310
500	350	280	300	200

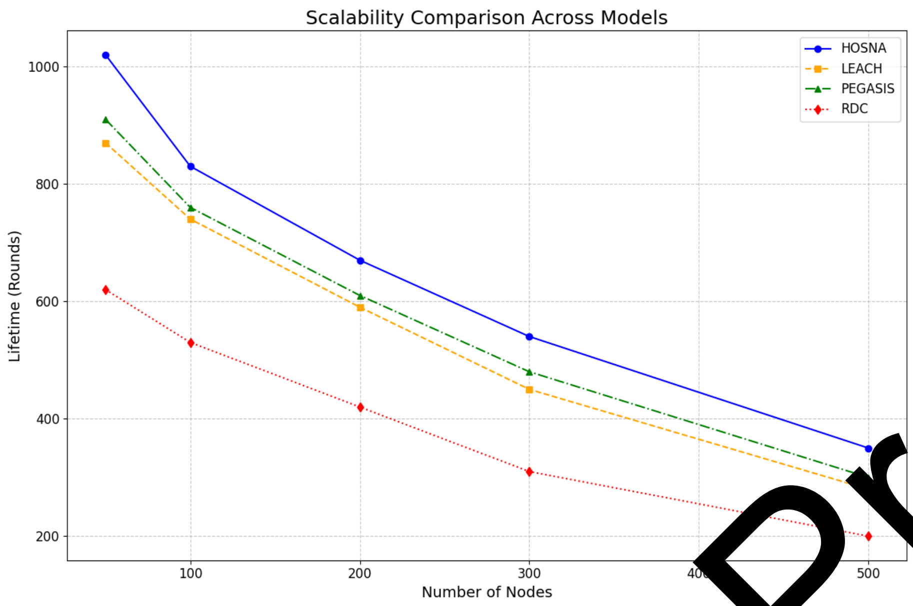

Fig 9. Scalability Comparison across Models

Table 7 and Figure 9 gives the relative performance of the HOSNA, LEACH, PEGASIS and RDC models with regards to scalability and again the table also shows that as the number of nodes increases HOSNA outperforms the others. HOSNA can achieve a total of 50 nodes network lifetime of 1020 rounds while consuming less energy than LEACH at 870 rounds, PEGASIS at 910 rounds, and RDC at 620 rounds. As the number of nodes increases to 100, 200, 300, and 500, there is a clear indication that the proposed HOSNA protocol has shorter lifetimes of 830, 670, 540, and 350 respectively. However, in similar scenario, LEACH manages to complete 740, 590, 450 and 280 rounds for PEGASIS performs only 760, 610, 480 and 300 rounds. RDC results in lowest efficiency rates with the lifetime of 530, 420, 310, and 200 rounds. This scalability advantage also supports evidence of the efficiency of HOSNA in terms of resource control and performance independence from the size of the network, making HOSNA suitable and reliable for large-scale applications in smart agriculture.

5. Conclusion And Future Scope

The HOSNA model delivers significant advancements in WSN performance for smart agriculture, achieving a 94.0% data accuracy compared to LEACH (90.0%), PEGASIS (86.0%), and RDC (70.0%). Its hybrid optimization framework ensures lower energy consumption and extended network lifetime, critical for large-scale and remote agricultural fields. The system's predictive capabilities, powered by LSTM, further enhance its efficiency by enabling proactive sensor activation. By reducing energy usage by 24% compared to LEACH, HOSNA supports sustainable and cost-effective operations. The improved accuracy ensures precise environmental monitoring, aiding decisions like irrigation scheduling and pest control. Future scope includes enhancing the scalability of HOSNA to accommodate larger, heterogeneous sensor networks with diverse energy and communication requirements. Incorporating renewable energy sources, such as solar panels, could make the system entirely sustainable. Additionally, exploring the integration of blockchain for secure and transparent data transmission could open new opportunities. Real-world deployments across diverse agricultural scenarios can further validate HOSNA's reliability and adaptability.

Declarations

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Conflicts of interest: The authors declare that they have no conflict of interest
Availability of data: The datasets generated during and/or analysed during the current study are not publicly available but are available from the corresponding author on reasonable request.
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