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Wireless Sensor Network Energy optimization by Intelligent Water Drop Algorithm

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Abstract: Energy efficiency remains a critical challenge in Wireless Sensor Networks (WSNs), as sensor nodes operate on limited power sources and frequent battery replacement is often impractical. Energy optimization by reducing the communication cost directly increases the life span of WSN. So researchers proposed various work but dynamic behavior of node is a major issue. This paper proposed a model that cluster the nodes in dynamic environment without any prior training and reduces the communication cost. Clustering was done by bio-geographical algorithm an Intelligent Water Drop. In this algorithm intelligent water drop was identified and clustering was done. This operation is performed after fix number of rounds so movement of nodes were considered. Experiment was done on different environment with heterogeneous nodes. Results demonstrate that IWNO significantly improves network lifetime, increases packet transfer rates, and delays the first node's energy depletion compared to existing model.

***IndexTerms* - Energy Optimization, WSN, Genetic Algorithm, WSN.**

I. INTRODUCTION

Wireless Sensor Networks (WSNs) hold immense promise for enhancing human life and advancing environmental monitoring through the use of sensor nodes. A major challenge in deploying these nodes lies in their reliance on small, low-power batteries, which restrict their operational lifetime. Various integration techniques have been introduced to overcome distance and performance limitations, helping to extend network life while simultaneously reducing node size [1]. WSNs provide several notable benefits, including scalability, ease of installation, flexibility, and the ability to self-organize [2]. Despite these advantages, communication in WSNs is highly energy-consuming since each node serves as a relay, forwarding packets until the data reaches the base station (BS).

In contrast to wired networks, WSNs encounter additional limitations such as restricted power supply, small memory, etc. [3]. Because sensor nodes typically depend on compact batteries with very limited capacity [4], energy efficiency becomes vital for extending network longevity. In extreme scenarios, such as volcano monitoring, battery replacement is impractical, making long operational duration indispensable [5].

Most WSNs are deployed in concealed or remote areas, powered solely by small, non-replaceable batteries. Managing energy usage in such systems is one of the greatest challenges. Interestingly, contrary to general perception, energy consumption alone does not determine overall network efficiency [6]. For this reason, the development of energy-aware routing strategies has become essential for reducing battery consumption [7]. Several techniques spanning the physical, data link, and network layers have been proposed to optimize data transmission and minimize energy waste. A key design challenge is achieving balanced energy consumption among all nodes, as usage often varies with application demands. Moreover, since many deployments are in harsh environments, nodes cannot be recharged or replaced [8].

Among the different approaches to improve energy efficiency, clustering mechanisms are considered highly effective. In clustering-based WSNs, smart nodes (SNs) are grouped within communication ranges and connected to specialized nodes called cluster heads (CHs). CHs are responsible for aggregating data, eliminating redundancy, and forwarding the compressed information to a distant sink [9]. However, clustering in WSNs is computationally intensive and classified as an NP-hard problem. To address this complexity, meta-heuristic algorithms are widely applied, offering robust solutions to such optimization challenges [10]. Beyond WSNs, meta-heuristic techniques are also applied in real-world domains, including solving the traveling salesman problem, detecting cardiac arrhythmia, and other biomedical applications [11].

II. RELATED WORK

S. S. Elashry et al. [12] introduced an enhanced version of the Reptile Search by integrating it with a chaotic mapping mechanism. Traditional RSA, similar to many meta-heuristic algorithms, often suffers from premature convergence and entrapment in local minima. By embedding chaotic maps, the proposed Chaotic model increases population diversity and improves the ability to escape local optima. Within the context of WSNs, proposed model is employed to select an optimal set of cluster heads, thereby minimizing energy consumption and prolonging network lifetime.

M. Haris et al. [13] proposed a clustering technique based on Particle Swarm algorithm with a double-exponential adaptive inertia weight mechanism. This adaptive weighting balances global exploration and local exploitation, helping avoid early convergence and improving CH selection accuracy. The method classifies nodes into cluster members, CHs, and free nodes to maximize cluster head selection efficiency in IoT-enabled WSNs. Residual energy is a key factor in dynamically determining the number of clusters, and nodes are grouped into balanced clusters where high-energy nodes are preferentially chosen as CHs based on their location, thus improving overall energy efficiency.

M.-R. Mortada et al. [14] extended their work to Energy-Harvesting Cognitive Wireless Sensor Networks, where nodes function as Secondary Users (SUs). They proposed a LIBRO-based framework for EH-CWSNs to address energy limitations and reduce the need for frequent battery replacements, making the system more suitable for deployment in harsh environments. A key contribution of LIBRO is its ability to minimize cooperation among nodes during routing, which helps protect Primary Users from interference caused by secondary transmissions. The framework adapts LIBRO for spectrum sensing and optimizes network parameters so that energy consumption remains below the energy harvested from EH units. Using a multi-objective optimization approach, the model balances packet delivery latency, network throughput, energy usage, and PU collision probability, creating a sustainable self-powered WSN.

J. Jayachandran et al. [15] presented a hybrid routing approach for border surveillance WSNs that combines Energy-Efficient Routing with a Cluster-based Genetic Harris Hawk Algorithm. Designed for large-scale distributed networks, the objective is to conserve node energy while identifying efficient routing paths through fitness-based optimization. By leveraging the Genetic Harris Hawk Optimization process—including selection, crossover, and mutation operators—the method ensures low-latency routing, reduced energy consumption, and an extended network lifetime.

Chandane, M. M. et al. [16] proposed a simulation framework for WSNs to evaluate energy-aware routing protocols. Their survey highlighted that Minimum Total Transmission Power Routing and Minimum Battery Cost Routing are two prominent protocols capturing the trade-offs between battery efficiency and overall network lifetime. The model was implemented using Qualnet 4.5 to analyze the performance of models, providing a foundation for future enhancements aimed at extending WSN longevity.

Sharma, T. et al. [17] developed an energy-efficient routing algorithm with anomaly detection capabilities to improve both stability and lifetime of heterogeneous WSNs. The approach incorporates three anomaly detection techniques—Random Forest, K-Nearest Neighbor, and Local Outlier Factor—to enhance monitoring accuracy. The network is divided into two regions based on node location and energy levels to better balance load and energy consumption. In the first region, clustering is performed with an objective function called Node Performance Score (NPS) guiding efficient CH selection. In the second region, relay nodes are deployed to support effective data collection, further extending the overall lifespan of the network.

Some of major existing issues are:

Premature Convergence in Meta-Heuristics – Algorithms like RSA and PSO often suffer from local optima trapping, leading to suboptimal cluster head (CH) selection and reduced network performance.

Scalability Challenges – Most proposed models are tested on small or medium-scale WSNs. Their effectiveness and stability in large-scale, real-time deployments remain uncertain.

Energy Constraints in Dynamic Environments – While energy-efficient clustering and routing are addressed, unpredictable energy variations still cause instability in network operations.

High Computational Overhead – Advanced meta-heuristic and hybrid models, such as Genetic Harris Hawk optimization, often involve complex operations (crossover, mutation, chaotic mapping) that may not be suitable for resource-constrained WSN nodes.

III. PROPOSED WSN OPTIMIZATION MODEL

Energy optimization of WSN nodes done by reducing the hardware consumption cost and by reducing the communication steps. This paper has work on communication based energy optimization by Intelligent Water Drop Network Optimization (IWNO). Flow of whole model is shown in fig. 1, each block was detailed in this section of paper. Explanation was done by various equations and notation used in work.

Develop Network

Paper has done experimental work on virtual nodes, where each node has its own battery life e and position p. In this network n number of nodes were place in A area having mxm dimension in meters. Each node have transmitter and receiver. Nodes have common energy loss in receiving data/signal but have different energy requirement in transmitting p data for d distance [11, 12, 14].

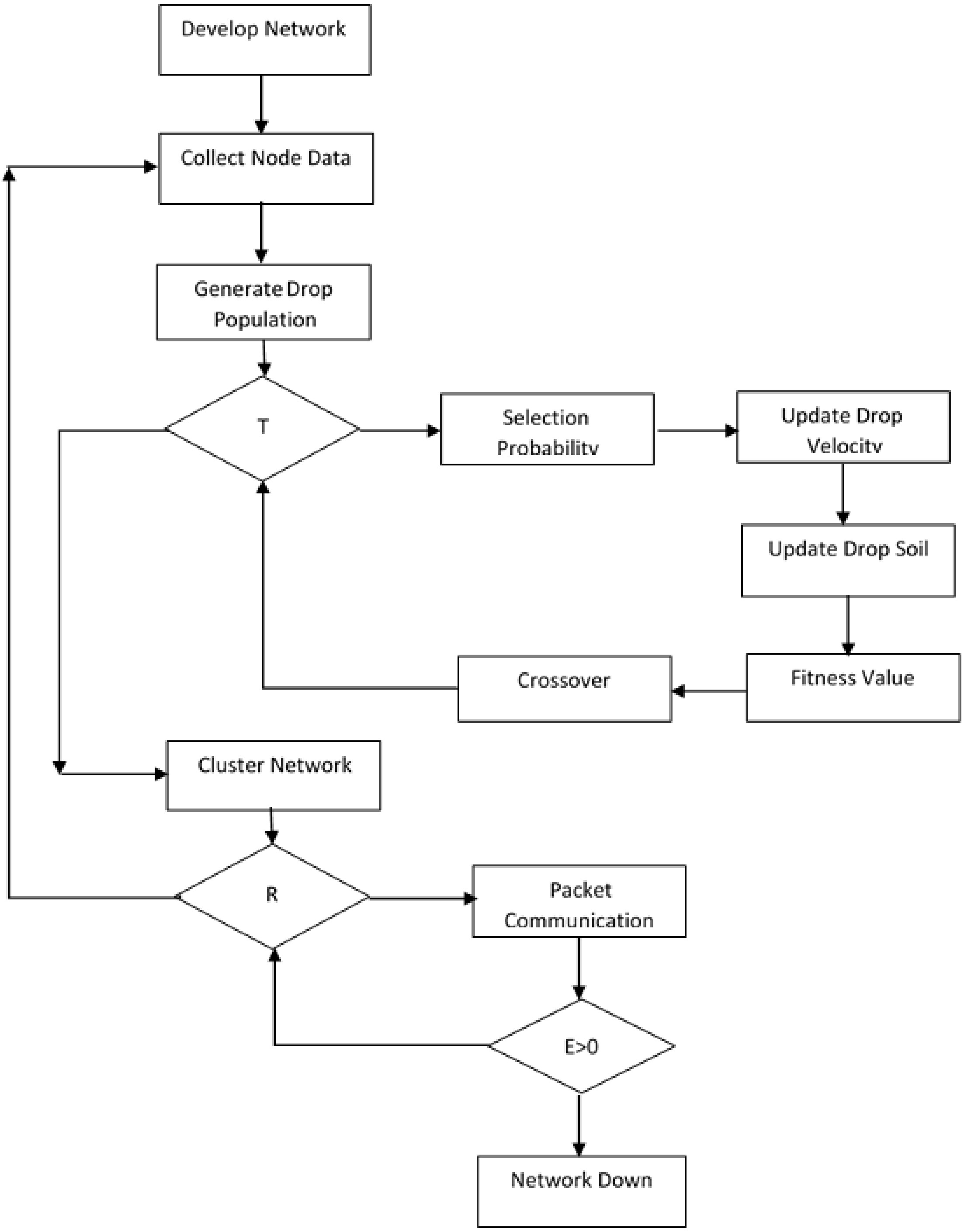

Fig. 1 IWNO model flow chart.

ETx(L,d) = Eelec x L+ a x Lx db

ERx(L,d) = Eelec x L

where:

- L = length of the information in bits
- d = distance between the source and destination node
- Eelec = energy consumed per bit for processing
- a and b = parameters depending on distance ddd

The values of a and b depend on whether the distance ddd is less than or greater than a threshold distance d0d_0d0:

- If d⩽d0d \leq d_0d⩽d0: a=afsa = a_{fs}a=afs (free-space amplifier cost), b=2b = 2b=2
- If d>d0d > d_0d>d0: a=aampa = a_{amp}a=aamp (multi-path amplifier cost), b=4b = 4b=4

Here, afsa_{fs}afs and aampa_{amp}aamp are the amplifier energy costs. For long-distance communication (d>d0d > d_0d>d0), significantly higher energy is required by the amplifier.

Collect Node Data Each node has its own set position and energy level in each round hence data is value set include position in A and e value [9,10]. Further based on live nodes cluster count vary. Hence for n number of nodes in A area k number of cluster count estimate by

$$K = \sqrt{\frac{n \times \varepsilon_{fs} \times A^2}{2\pi(2E_{elec} + E_A)}}$$

Where ε_fs represents the amplifier power consumption under free-space conditions, and E_A denotes the energy required for nodes to aggregate or fuse k-length data. This formula ensures balanced clustering that minimizes overall energy consumption.

Clustering by Intelligent Water Drop

The clustering process is modeled using the Intelligent Water Drop (IWD) algorithm, where each sensor node behaves as a "water drop." A graph structure is constructed where the nodes act as drops and the distances between them form the edges of the graph. In IWD terminology, the edges are referred to as "soil." The fundamental principle is that a water drop moves from one node to another along paths with minimal soil, as excessive soil slows the velocity of a drop. Thus, nodes that share greater similarity exhibit lower soil values, and clusters are formed by grouping such nodes.

The Water Drop Graph (WDG) is represented as a complete graph of size N × N, where N is the number of nodes. Each edge is assigned a weight in the form of soil S(i,j), estimated as the product of the Euclidean distance between nodes N_i and N_j multiplied by a scaling constant α.

$$Soil(i,j) = Euclidian(N\_i \ , N\_j) * \alpha$$

Static and dynamic parameters are initialized prior to algorithm execution, including soil updating parameters ($S_1 = 1$, $S_2 = 0.01$, $S_3 = 1$) and velocity updating parameters ($V_1 = 1$, $V_2 = 0.01$, $V_3 = 1$). Additionally, global and local soil constants (β_L and β_G) are set to 0.9, with flexibility to vary depending on algorithmic requirements.

Generate population Population generation involves creating a collection of chromosomes, where each chromosome corresponds to a possible clustering solution. Each chromosome contains a set of cluster centers, represented by nodes. For instance, a potential solution may be written as Chromo = {n_1, n_2, n_9, …, n_k}, where k is the number of clusters in the network. This is expressed through the population generation function:

Wp<-Generate_Population(k,w)

Here, W_p denotes the water drop population, consisting of w drops, each containing k cluster centers. The selection probability defines the likelihood of a water drop moving from one node to another among the possible N–1 candidates. This probability SP(i,j) is calculated as:

Selection Probability the likelihood of a water drop moving from one node to another among the possible N–1 candidates. This probability SP(i,j) is calculated as [19]:

$$\mathrm{SP(i,j)} = \frac{\mathrm{FS(i,j)}}{\sum_{\mathrm{k=1}}^{\mathrm{N}} \mathrm{FS(i,k)}}$$

$$\mathrm{FS(i,j)} = \frac{1}{\delta + \mathrm{GS(i,k)}}$$

$$\mathrm{GS(i,j)} = \begin{cases} \mathrm{soil(i,j)} & \text{if } \min(\mathrm{soil(i,all\ element)}) > 0 \\ \mathrm{soil(i,j)} - \min(\mathrm{soil(i,all\ element)}) & \text{otherwise} \end{cases}$$

Update Velocity Update velocity of the ith drop moving toward jth node by below formula:

$$\mathrm{V(t+1)} = \mathrm{V(t)} + \frac{\mathrm{V_1}}{\mathrm{V_2} + \mathrm{V_3} * \mathrm{Soil(i,j)}^2}$$

Update Soil Update velocity of the ith drop moving toward jth node by below formula:

$$\Delta\mathrm{S(i,j)} = \frac{\mathrm{S_1}}{\mathrm{S_2} + \mathrm{S_3} * \mathrm{T(t+1)}^2}$$

$$T(t+1) = \frac{HD}{V(t+1)}$$

HD is heuristic durability a constant value range in 0-1.

$$Soil(i,j) = (1 - \beta_L) * Soil(i,j) - \beta_L * \Delta\mathrm{S(i,j)}$$

Fitness Function

The fitness function evaluates clustering efficiency based on energy consumption. It is defined as the total energy required to transmit one packet from all non-cluster nodes to their cluster centers and then from cluster centers to the base station. Non-cluster nodes expend energy ET_nc, cluster centers expend energy ER_c for reception, and transmit energy ET_c to forward data to the base station. Thus, the fitness function is expressed as:

Fw□ETnc*n+ (ERc+ ETc)*k

Global Crossover To enhance population diversity, a global crossover mechanism is applied, inspired by genetic algorithms. The best-performing chromosome (based on fitness) is selected as a common parent for crossover operations with other chromosomes. During crossover, a random cluster center from the best chromosome replaces the corresponding cluster center in another chromosome, provided no duplication occurs. This process ensures improved offspring solutions. The crossover operation is expressed as:

Wp□Crossover(Wp, Fw, SP)

Population Updation Following crossover, population updating occurs. If the offspring chromosome has a better fitness than its parent, it replaces the parent in the population; otherwise, the parent is retained. This ensures that the population size remains constant while progressively improving solution quality.

Cluster Network

After completing T iterations of the genetic algorithm, the population was updated to its final optimized form. The chromosome exhibiting the best fitness value was selected, and this solution provided the most suitable set of cluster centers. Based on these centers, all remaining nodes in the network were systematically assigned to clusters. The assignment relied on feature similarities and distance metrics, ensuring efficient clustering that minimized energy usage and enhanced overall communication performance.

Wc<-Cluster(n, Fw)

Packet Communication

In this work packets were communication from sensor nodes to base station based on cluster center hierarchy. Nodes having energy do the communication and energy value were decrease as per transmission, receiving of packets. After R number of rounds clustering of node were further processed to get new cluster center nodes.

Proposed Algorithm

Input A, n

Output: C

1. [n e p]□Initialize_Network(n,A)
2. K□Estimate_Cluster_network(n,A)
3. Soil(i,j)= Euclidian(N_i ,N_j)*α
4. Wp□Generate_Population(k,w)
5. Loop 1:t
6. SP□Selection_Probability(Wp,n,e)
7. Fw□ETnc*n+ (ERc+ ETc)*k
8. Wp□Crossover(Wp, Fw, SP)
9. EndLoop
10. Fw□ETnc*n+ (ERc+ ETc)*k
11. Wc□Cluster(n, Fw)

IV. EXPERIMENT AND RESULTS

The IWNO model and the comparative CGHHOA model [15] were developed and tested using MATLAB software, chosen for its effectiveness in simulating optimization algorithms and clustering techniques. Experiments were executed on a system equipped with an Intel Core i3 6th generation processor and 4 GB RAM, providing adequate computational resources for iterative simulations. This setup ensured fair performance evaluation of both models under identical conditions, enabling reliable analysis of clustering efficiency, energy optimization, and overall network performance.

Results:

Table 1 Comparison of models on the basis of total number of rounds in network.

Nodes	Network Area m^2	CGHHOA	IWNO
70	10000 (100x100)	24333	30703
80	10000 (100x100)	20531	31144
90	10000 (100x100)	19138	31187
100	10000 (100x100)	19355	31020
100	22500 (150x150)	14304	30559

Table 1 shows number of rounds taken by the models in different environmental setup. It was found that use of water drop algorithm has increases the round count in same environment. Clustering was done efficiently it directly increases the rounds by 36.82% as compared to existing model. It was also found that repetitive clustering increases the work performance.

Table 2 Comparison of models on the basis of total packet transfer in network.

Nodes	Network Area m^2	CGHHOA	IWNO
70	10000 (100x100)	623579	660892
80	10000 (100x100)	697403	761890
90	10000 (100x100)	806568	814947
100	10000 (100x100)	859511	895463
80	22500 (150x150)	655086	670645

Number of packet transfer for each set of experiment was shown in table 2. It was found that increase in number of nodes in same area has increases the packet count. Further use of intelligent water drop algorithm for clustering of nodes has increases the packet count by 4.2% as compared to CGHHOA model.

Table 3 Comparison of models on the basis of first node discharge rounds in network.

Nodes	Network Area m^2	CGHHOA	IWNO
70	10000 (100x100)	11653	15681
80	10000 (100x100)	13186	14715
90	10000 (100x100)	9572	12929
100	10000 (100x100)	8242	13949
80	22500 (150x150)	2839	7485

Table 3 shows comparison of first node discharge rounds of WSN energy optimization models. As per environment work has reduces the energy requirement and this increases the first node discharge round count value by 29.75%. It was also found that with increase in number of nodes first node count value get decreases.

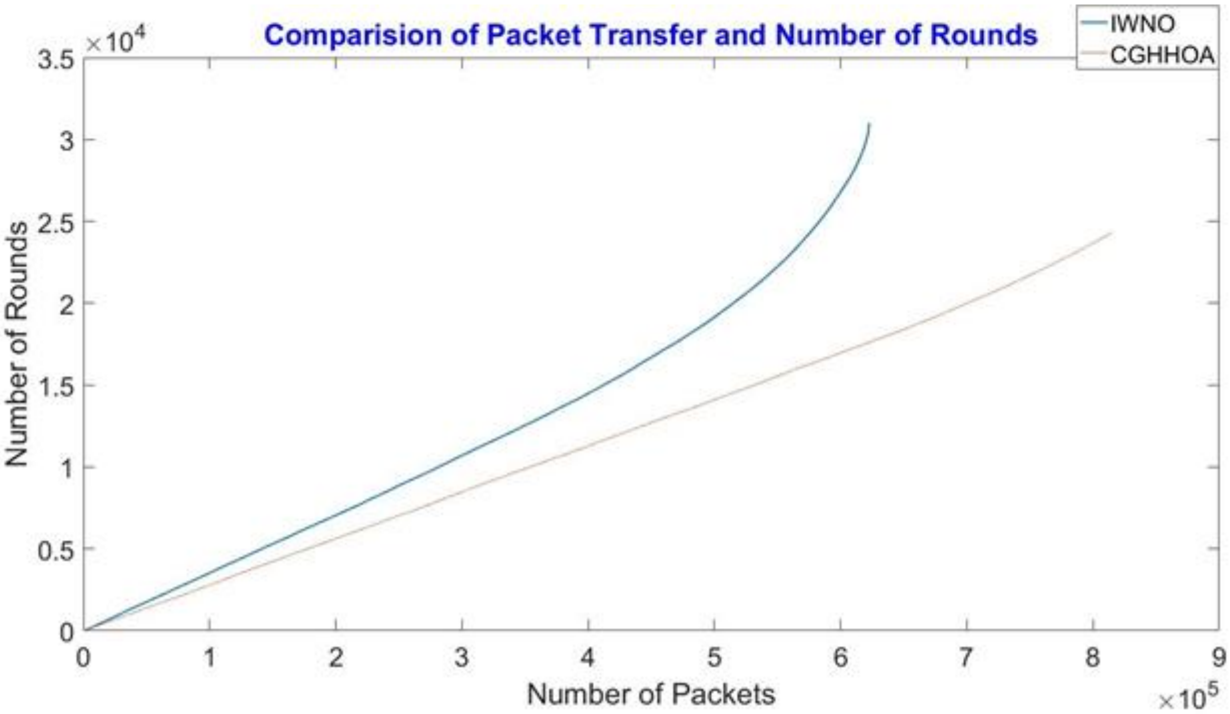

Fig. 2 Comparison of number of packets sent and number of rounds for each model under 70 nodes and 100x100 area.

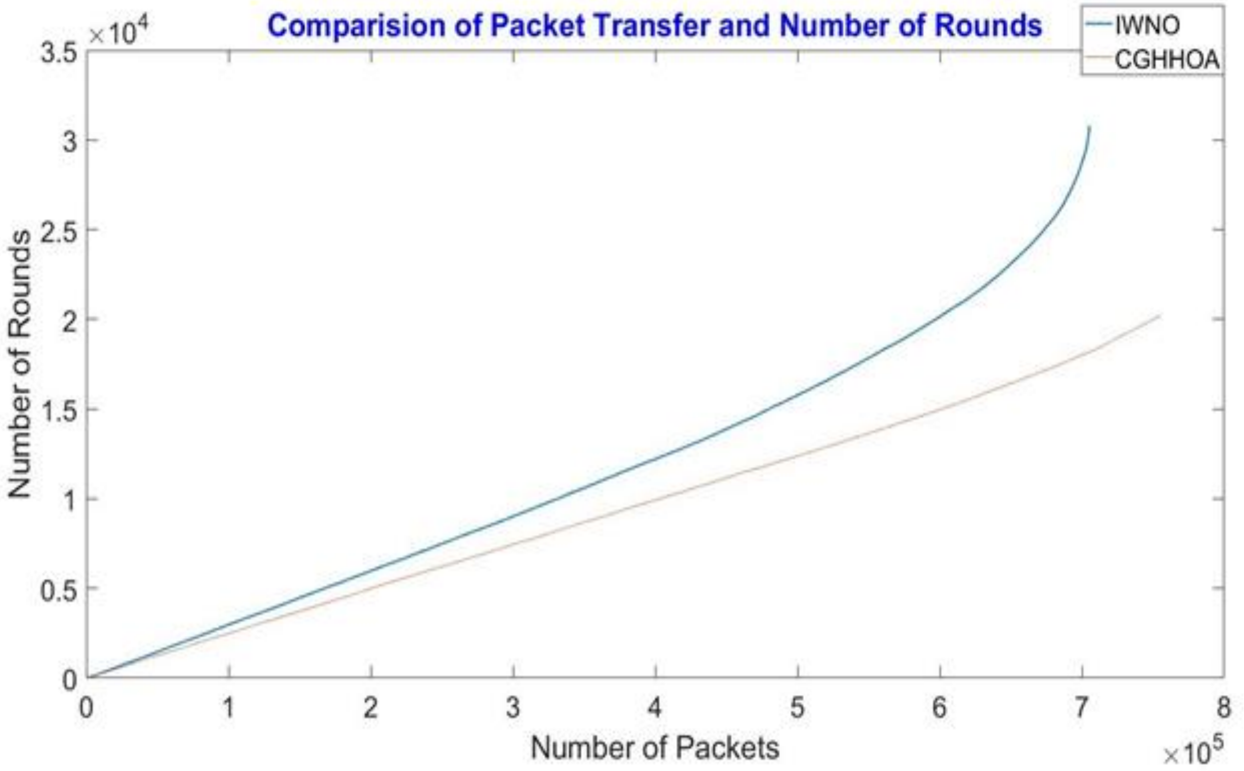

Fig. 3 Comparison of number of packets sent and number of rounds for each model under 80 nodes and 100x100 area.

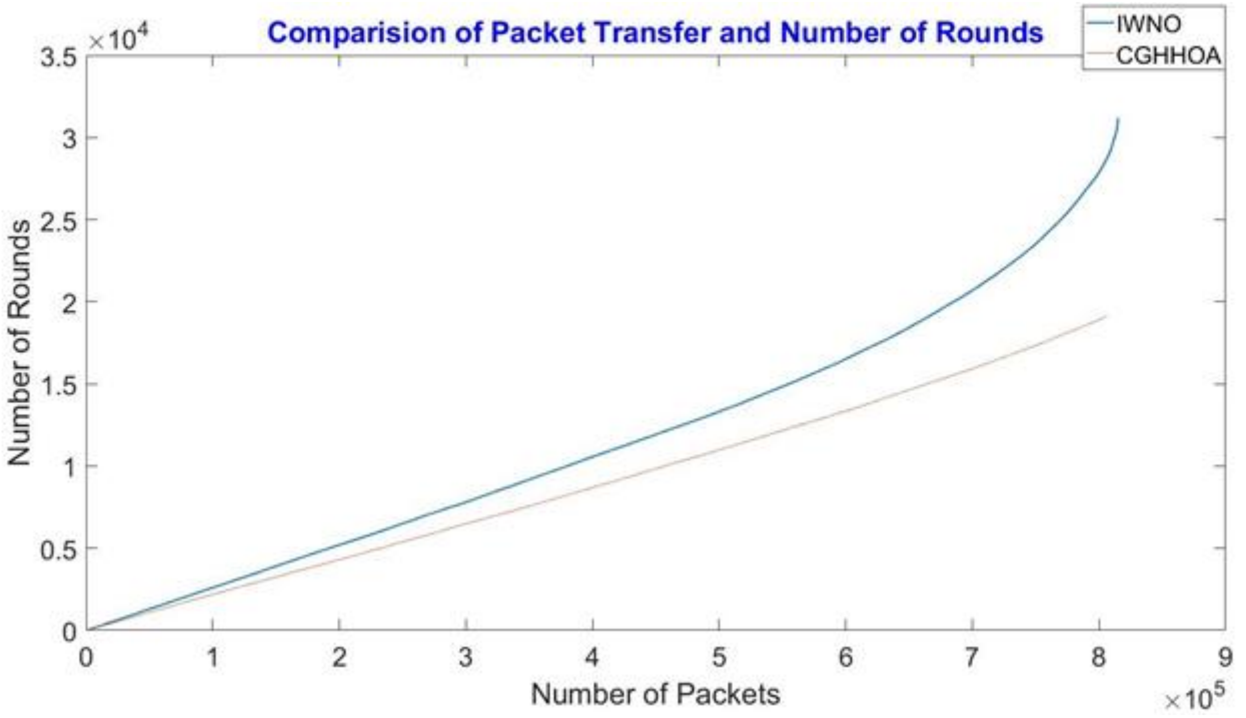

Fig. 4 Comparison of number of packets sent and number of rounds for each model under 90 nodes and 100x100 area.

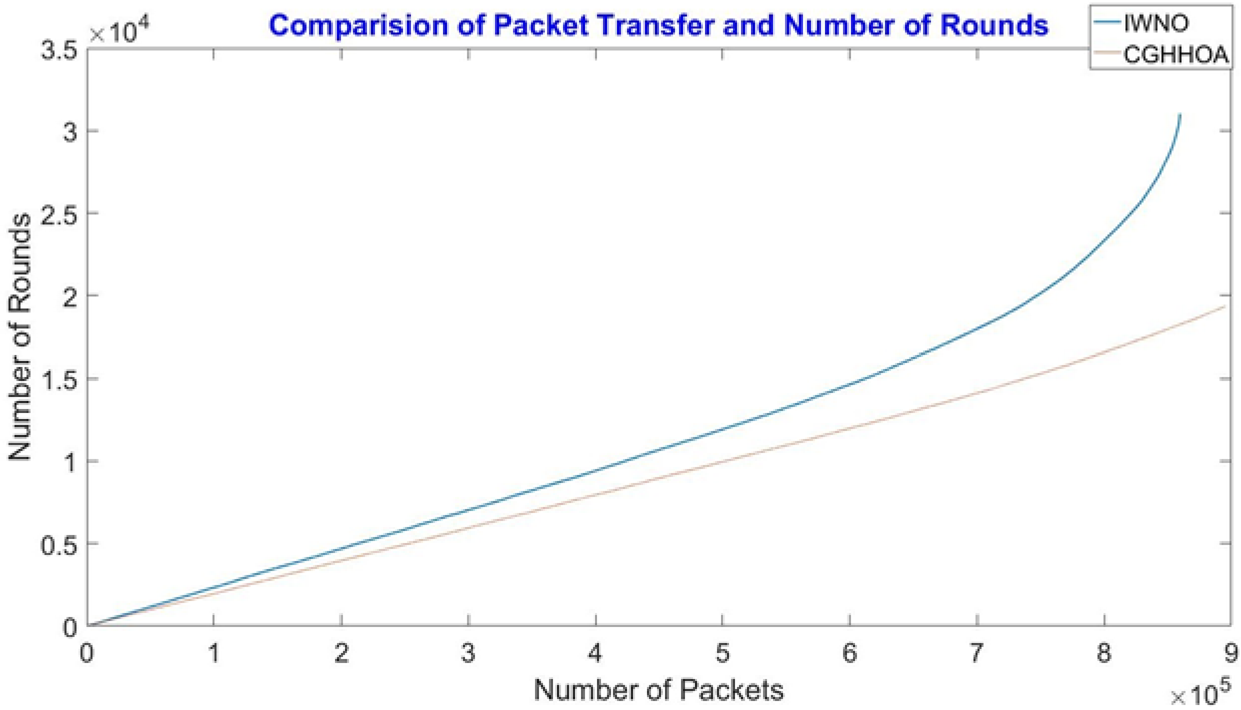

Fig. 5 Comparison of number of packets sent and number of rounds for each model under 90 nodes and 100x100 area.

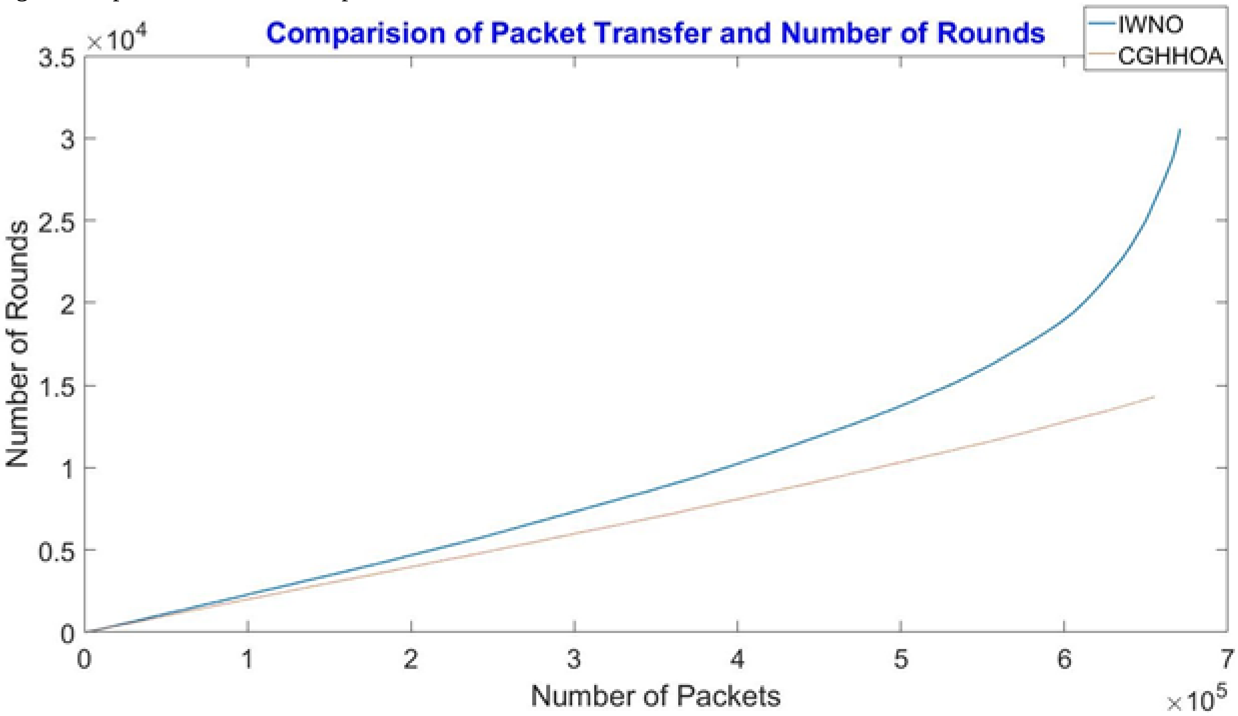

Fig. 6 Comparison of number of packets sent and number of rounds for each model under 100 nodes and 100x100 area.

Fig. 2, 3, 4, 5 and 6 shows that proposed IWNO model has increases the packet count at each round. Clustering of nodes in dynamic environment has increases the rounds and packets both. Further in last set of rounds sharp curve shows that most nodes were lost so packets were less but rounds were keep increasing.

V. CONCLUSION

This study introduced IWNO as an efficient clustering-based optimization algorithm for energy conservation in WSNs. By simulating sensor nodes as water drops and leveraging soil-based graph modeling, the algorithm effectively balances energy usage across nodes while minimizing redundant communication. The integration of genetic crossover further enhances the adaptability of the clustering process, ensuring improved convergence and robustness. Experiment was done on different environment and it was found that model has increases the round count by 36.82% and packet count by 4.2%. Further use of intelligent water drop has reduces the energy waste and increases the first node discharge by 29.75%. In future scholars can involve learning of packets that reduces the cost.

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