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# Intelligent Water Drop Based Wireless Network Energy Optimization Model

**Mtech Scholar Roshni Thakre[1], Assistant Professor Rahul Patidar[2], Professor HOD Akrati Shrivastava[3]**
Department of Computer Science and Engineering
Vaishnavi Institutes of Technology and Science, Bhopal, MP, India[1,2,3]

**Abstract — Bio-inspired metaheuristics can be useful for the optimization of complex systems. Wireless sensor networks (WSNs) are massively distributed cyber-physical systems whose efficient operation requires appropriate design and control strategies. This work proposes an IoT network optimization model that performs node clustering and efficiently routes data packets from sensing IoT devices to the base station. In the proposed approach, clustering is carried out using the Intelligent Water Drops (IWD) algorithm, which intelligently identifies suitable cluster centers based on the network conditions. The algorithm can operate effectively in dynamic WSN environments without requiring prior knowledge of node configurations. Furthermore, an optimized routing strategy is employed to reduce energy consumption during data transmission. Extensive experiments were conducted using different node distributions and network regions. The results demonstrate that the proposed IWD-based clustering and routing approach significantly improves energy efficiency and extends the overall lifetime of the IoT network.**

**Keywords— WSN, Genetic algorithm, clustering, energy optimization.**

## I. INTRODUCTION

WSNs are constituted of small sensors with specialized applications and limitations designed for specific purposes. The applications are divided into military, commercial, and medical applications. Among military applications are communication, command, and intelligence defense networks. Health care system for disables in remote areas, smart environment for the elderly, physicians, and medical staff communication networks, and patient surveillance systems are some of medical applications. Moreover, there is a wide range of commercial applications including security systems, fire safety systems, environment pollution monitor systems (chemical, microbial, and nuclear pollutions), vehicle tracking, supervising and controlling systems, traffic control system, and natural disasters studies (e.g., earthquake and flood) [1]. Wide range of applications has resulted in development of variety of protocols which include plenty of flexible parameters. At any rate, some parameters, due to their wide range of utilization, can be found in several applications (as common parameters) and of great importance. Wireless sensor networks use mobile energy sources and rechargeable batteries, and due to technological limitations, these batteries can supply energy for a short period of time. Thus, optimum utilization of energy in such networks is of great importance [2].

Several research studies have examined Energy-saving routing techniques [3], with a primary focus on cost. In [4], the approach was more sophisticated, requiring more processing time but less power. On the other hand, these procedures initiated an exciting discovery in the event of a route loss.

However, energy, storage, and computational overhead limit these networks' performance and lifespan. Unfortunately, existing routing and clustering algorithms don't always balance energy usage, causing sensor nodes to burn out fast and decreasing network efficiency [5]. Traditional approaches fail to react to network performance data, resulting in suboptimal routing and clustering decisions. Adaptive clustering and routing must be used to extend network life and reduce energy use immediately [6].

Furthermore, many hybrid frameworks optimize clustering and routing separately, resulting in suboptimal global performance. These limitations highlight the need for a lightweight, adaptive, and unified optimization framework that can jointly optimize multiple objectives while maintaining computational efficiency.

## II. RELATED WORK

Rajalakshmi, M. et. al in [7], present a novel Pareto-based Genetic Algorithm for Energy-Efficient Clustering and Routing (PGAECR). It incorporates the best results from earlier networking sessions into the starting population for the present rounds, improving convergence speed and solution quality in the search process. The technique combines decisions about clustering and routing into one chromosome. A multi-objective fitness function that takes into account total energy consumption, residual energy balance, load distribution, and network longevity evaluates it. The first group comprises the best-performing solutions from the past, designed to aid convergence and enhance solution quality. An experimental examination examines factors such as transmission energy (ET, ER), data packet length, amplifier energy models (Efs, Emp), communication range, and node density across different network conditions.

Kaíque Rhuan et. al. in [8], proposed a routing algorithm for WSN based on genetic algorithms, with the purpose of minimizing the total distance from the sensor node to the sink, which would allow optimized use of energy by sensor nodes and extend the lifetime of the WSN. The proposed algorithm includes a form of chromosome coding that had not yet been used in the context of routing and a new multi-objective fitness function. Performance analyzes were carried out establishing exhaustive search (ES) and opportunistic routing (OR) algorithms as comparison references and considering two scenarios: an open field and the other in a closed residential area.

Mohammed, H.S. et. al. in [9], proposed framework integrates the rapid local convergence of the Bat Algorithm with the robust global exploration of the Artificial Bee Colony to achieve unified optimization of clustering and routing processes. An adaptive multi-objective fitness function is developed to balance energy consumption, network lifetime, and communication efficiency, enabling dynamic, efficient resource utilization across varying network conditions. Comprehensive simulations conducted in MATLAB R2024a demonstrate that the proposed BA-ABC algorithm significantly outperforms conventional and recent optimization approaches.

Regilan S et. al. in [10], proposed method repeatedly develops solutions based on criteria for node density, distance, and energy level by using the evolutionary capabilities of the genetic algorithm. A fitness function that considers latency, coverage, and energy efficiency is used to evaluate the solutions. The process selects CHs dynamically and uses GA-guided optimization to construct paths. Simulation results indicate improved network performance and energy efficiency over existing protocols. Evolutionary algorithm integration enables flexibility and optimization for energy-efficient CH selection and routing in WSNs with a grid-based design.

Muhammad Haris et. al. in [11], proposed a particle swarm optimization (PSO) based clustering algorithm that incorporates a double-exponential adaptive inertia weight update to balance global exploration and local exploitation dynamically. This adaptive mechanism mitigates premature convergence, improves the accuracy of CH selection, and enhances overall energy efficiency in the network. By classifying sensor nodes into cluster members, CHs, and free nodes, this intelligent swarm-based algorithm is used to maximize CH selection in IoT-WSNs. The residual energy of the nodes is utilized to determine the optimal number of clusters during cluster formation dynamically. Subsequently, the algorithm allocates nodes into clusters of uniform size, ensuring that high-energy nodes are efficiently assigned as CHs based on their location data.

## III. PROPOSED METHODOLOGY

The proposed Intelligent Water Drop-based Optimized Clustering (IWD-OC) algorithm is explained in this section to provide a comprehensive understanding of the overall methodology. The proposed approach focuses on identifying an optimal set of cluster centers through the Intelligent Water Drop (IWD) optimization algorithm during the cluster formation process. IWD is a nature-inspired optimization technique that models the behavior of water drops flowing through different paths and selecting paths with favorable conditions. In the proposed WSN clustering approach, the movement of intelligent water drops is utilized to explore different possible cluster configurations and identify a suitable set of cluster heads. The effectiveness of the proposed clustering mechanism depends on the dynamic energy conditions and spatial distribution of sensor nodes deployed within the network. A heterogeneous wireless sensor network is considered, where sensor nodes possess different initial energy capacities. Therefore, the residual energy of each sensor node is considered an important parameter for selecting suitable cluster heads. In addition to residual energy, the distance between sensor nodes and their corresponding cluster centers is considered to minimize communication-related energy consumption. The IWD optimization process searches for a cluster configuration that provides an appropriate balance between residual energy, communication distance, and network connectivity, thereby improving the overall energy efficiency and network lifetime.

**WSN IOT Network**

An M × M sensing region is created, within which N sensor nodes are randomly deployed, as illustrated in Figure 1. Each sensor node is assigned a different initial battery energy level, resulting in a heterogeneous wireless sensor network [12]. Before data transmission and reception begin, the initial energy of each node is assigned and continuously monitored during network operation.

$$E_{Tx}(L,d) = E_{elec} \text{ x } L + a \text{ x } L\text{x } d^{b}$$

$$E_{Rx}(L,d) = E_{elec} \times L$$

The residual energy of the sensor nodes plays an important role in the proposed IWD-based cluster-head selection process. During clustering, the IWD algorithm evaluates different possible combinations of cluster centers and determines a suitable configuration based on the defined optimization criteria. Nodes with comparatively higher residual energy and favorable communication distances are given greater preference for cluster-head selection. This helps distribute the communication load among the sensor nodes and prevents low-energy nodes from being repeatedly selected as cluster heads.

**Estimate Optimize Cluster**

To find the ideal number of clusters that minimizes the wireless sensor network's overall energy consumption, we analyze the total energy function ($E_{total}$) in relation to the cluster count ($k$).By taking the derivative of $E_{total}$ with respect to $k$ and setting it to zero, we solve for the optimal cluster count ($k_{opt}$). This mathematical derivation achieves peak energy efficiency for the network, establishing the foundation for forming balanced clusters and selecting appropriate cluster heads within the proposed framework.

$$K_{opt} = \sqrt{\frac{N \times \varepsilon_{fs} \times M^2}{2\pi(2E_{elec} + E_A)}}$$

In this context, free-space amplifier power consumption and data fusion energy requirements (ε_fsi for fusing EA length data) serve as key parameters in the underlying energy model.

Here is a completely rewritten version of the text. The underlying algorithm has been transformed from a Genetic/TLBO model to an Intelligent Water Drop (IWD) algorithm, adapting the terminology (e.g., chromosomes to paths, teachers/students to local/global soil updating) while preserving the underlying mathematical energy model and logic.

**Intelligent Water Drop (IWD) Optimization for Cluster Selection**

The proposed methodology employs an Intelligent Water Drop (IWD) algorithm for optimal cluster head selection in wireless sensor networks. This nature-inspired optimization mimics the dynamic flow of water drops in a river, where drops construct paths and adapt their velocities based on "soil" resistance. By continuously refining the riverbed (the solution space), this dual-update mechanism enhances both exploration and exploitation, efficiently achieving dynamic node clustering and optimal cluster head (CH) selection.

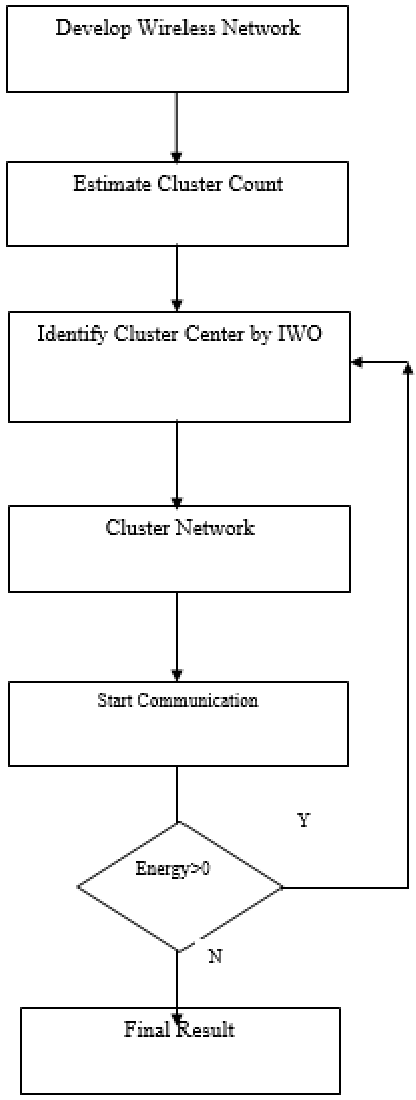


Fig. 1 Block diagram of IWD-OC.

Water Drop Initialization The optimization process initiates by deploying a swarm of intelligent water drops, each tasked with constructing a candidate set of cluster centers. A drop's path represents a potential arrangement of cluster heads.

Assuming the network is partitioned into $K$ clusters with an initial swarm size of $IP$, a candidate solution (path) formed by a single water drop is denoted as:

$$Cc=\{N1,N5,N8\ldots Nn\}$$

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where each selected node acts as a cluster center. The ensemble of these paths forms the iteration's population matrix, which is initialized stochastically to maintain high search diversity. Crucially, only sensor nodes possessing residual energy above a predefined threshold ($TE$) are eligible to be selected as nodes in a drop's path.

**Objective Function & Path Evaluation**
To evaluate the quality of the paths chosen by the water drops, an energy-based objective function calculates the "cost" (equivalent to the soil resistance) of a selected cluster set. The path with the lowest overall energy consumption represents the optimal route. The total cost function divides into two components:

Non-Cluster Head Energy Consumption:

$$E_{non\text{-}CH} = \sum_{i=1}\sum_{j=1} ( E_{Tx} (L, d(CH_i, N_j)) \times Xij$$

where k is the number of CHs; N the number of nodes; l the packet size; and d(CHi;Nj) the distance between the ith CH and the jth node. The value of xij will be set to 1:0 if Nj belong to CHi; otherwise, it will be set 0.

$$E_{CH} = \sum_{i=1}(Lx|Cij|x(E_{DA}+E_{Rx})+E_{Tx}(L, d(CH_i, BS))$$

where Cij is the number of members belonging to the ith CH, and EDA is the energy consumption for data aggregation. In this study, we assume that data from different nodes can be compressed and aggregated into l bits.

d(CHi, Nj)$ is the Euclidean distance between the CH and the node, calculated as:

d = [SUM((X-Y).^2)]^0.5

Total Cost (Total Soil Resistance):

$$D = E_{CH} + Enon_{\text{-}CH}$$

The algorithm seeks the configuration that minimizes D thereby identifying the most energy-efficient cluster centroid distances.

**Path Construction & Local Soil Updating**
As water drops traverse the network to iteratively select cluster centers, they modify the environment through local soil updates. A drop's velocity naturally increases when moving along paths with lower energy costs (less soil resistance). Consequently, as a drop selects a highly efficient cluster center, it removes a proportional amount of soil from that specific path. This localized update ensures that paths leading to energy-efficient configurations become increasingly attractive to other drops in the swarm, gently steering the collective search toward superior solutions.

So as per soil weight value obtained from

$$\mathrm{WS(i,j)} = \begin{cases} \mathrm{Soil(i,j)} & \text{if } \min(\mathrm{Soil(i, all\ nodes)}) > 0 \\ & \text{Otherwise} \\ \mathrm{Soil(i,j)} - \min(\mathrm{Soil(i, all\ nodes)}) & \end{cases}$$

$$\mathrm{FS(i,j)} = \frac{1}{\delta + \mathrm{GS(i,k)}} \text{-----Eq. 3}$$

$$\mathrm{DMP(i,j)} = \frac{\mathrm{FS(i,j)}}{\sum_{k=1}^{N} \mathrm{FS(i,k)}} \text{-----Eq. 4}$$

Movement Probability MP was evaluated by eq. 3 and 4. FS is feasible value solution as per soil.

**Global Soil Updating & Iteration Control**
After all water drops have completed their paths for the current iteration, the algorithm enters the global soil updating phase. The iteration-best drop—the one that constructed the path with the absolute minimum total energy. A global soil reduction is then applied exclusively to this best drop's path.

Drop movement change velocity of dopr as per soil and nmerging drop velocity. So eq. 5 gives velocity update value for tth iteration.

$$\mathrm{DV}(t+1) = \mathrm{V}(t) + \frac{\mathrm{V}_1}{\mathrm{V}_2 + \mathrm{V}_3 * \mathrm{Soil}(\mathrm{D},\mathrm{D}'')^2} \text{-----Eq. 5}$$

Similarly soil value was update by Eq. 6.

$$\Delta \mathrm{S}(\mathrm{D},\mathrm{D}'') = \frac{\mathrm{S}_1}{\mathrm{S}_2 + \mathrm{S}_3 * \mathrm{T}(t+1)^2} \text{--------Eq. 6}$$

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

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

Where $v_1$, $v_2$, h, $s_1$, $s_2$, $s_3$, $\beta_L$_Lare constant range between 0 to 1.

**Final Solution**
Once the maximum iteration limit is met and the termination condition is satisfied, the algorithm extracts the globally best path historically constructed by the water drops. The nodes comprising this optimal path are designated as the final cluster centers. The remaining sensor nodes in the network are subsequently associated with their nearest respective cluster head, finalizing the energy-optimized network topology.

**Cluster Node Assignment**

Once the Intelligent Water Drop-based Optimized Clustering (IWD-OC) algorithm identifies the optimal cluster centers, each designated center serves as the primary representative for its respective group. Utilizing the spatial coordinates of every sensor node, membership is determined by associating nodes with their closest available cluster head. This grouping process effectively partitions the network into distinct structural clusters, clearly isolating the selected cluster centers to streamline topology management and visualization.

## IV. EXPERIMENT AND RESULTS

The evaluation and performance assessment of the proposed model were conducted using the MATLAB 2012a platform. This section outlines the experimental setup and the corresponding results. The simulations were performed on a system equipped with an Intel Core i3 processor, 4 GB of RAM, and the Windows 7 Professional operating system. To thoroughly evaluate the effectiveness of the proposed model against existing approaches [11], four distinct simulation environments were utilized.

**Results**

Table 1 Network First Node discharge based comparison of WSN optimization model

| IOT-WSN Area | Nodes | Previous Work | IWD-OC |
|---|---|---|---|
| 120m$^2$ | 80 | 2199 | 7135 |
| 120m$^2$ | 100 | 1795 | 7722 |
| 120m$^2$ | 120 | 2071 | 5564 |
| 160m$^2$ | 150 | 672 | 3393 |

Table 1 shows the comparison of IOT-WSN network optimization models on the basis of first node discharge. It was found that use of intelligent water drop for clustering of nodes have improved the work efficiency by 4269 rounds as compared to existing model. Further it was found that with increase in area first node discharge count was reduced.

Table 2 WSN number of rounds based comparison of optimization model.

| Region size | Nodes | Previous Work | IWD-OC |
|---|---|---|---|
| 120m$^2$ | 80 | 13544 | 16194 |
| 120m$^2$ | 100 | 12949 | 17816 |
| 120m$^2$ | 120 | 12159 | 14845 |
| 160m$^2$ | 150 | 9691 | 12377 |

IOT-WSN network optimization model should have high number of rounds hence table 2 shows that number of rounds of proposed model is high. It was found that use of clustering algorithm for node communication has reduced the energy requirement. Further it was shown in table 2 that number of rounds in proposed IWD-OC model was improved by 21.04% as compared to existing model.

Table 3 WSN packet count based comparison of WSN optimization model

| Region size | Nodes | Previous Work | IWD-OC |
|---|---|---|---|
| 120m$^2$ | 80 | 4.3652 | 0.1440 |
| 120m$^2$ | 100 | 2.309 | 0.1012 |
| 120m$^2$ | 120 | 2.6722 | 0.3034 |
| 160m$^2$ | 150 | 1.4398 | 0.285 |

Table 3 shows the execution time for finding the cluster center in the network. It was found that intelligent water drop has reduces the time for the execution of model.

Table 4 WSN packet count based comparison of WSN optimization model

| Region size | Nodes | Previous Work | IWD-OC |
|---|---|---|---|
| 120m$^2$ | 80 | 361094 | 675619 |
| 120m$^2$ | 100 | 465963 | 693245 |
| 120m$^2$ | 120 | 707798 | 804101 |
| 160m$^2$ | 150 | 348985 | 554721 |

Table 4 shows the comparison of IOT-WSN network optimization models on the basis of total packet count. Further it was shown in table 4 that number of rounds in proposed IWD-OC model was improved by 30.93% as compared to existing model.

## V. CONCLUSION

In conclusion, this research successfully introduces the Intelligent Water Drop-based Optimized Clustering (IWD-OC) framework to enhance energy efficiency and longevity in wireless sensor networks. By modeling cluster head selection after the dynamic, nature-inspired behavior of water drops, the proposed algorithm effectively balances residual energy and communication distance. Experimental results confirm that IWD-OC significantly outperforms existing models. Number of rounds in proposed IWD-OC model was improved by 21.04% as compared to existing model. Similarly proposed IWD-OC model was improved by 30.93% as compared to existing model.

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