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Optimized Energy-Efficient Cluster Routing in IoT-Enabled Wireless Sensor Networks via Mapdiminution-Based Training and Discovery Algorithm

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Abstract: The combination of WSNs and IoT technologies produces rapid mass-production yet requires energy-efficient routing protocols to fulfill the estimated demands. These protocols need further development to maintain continuous sensor node connections during their operational periods. The design of WSNs encounters a significant problem because sensor nodes have limited energy capabilities. The placement of NSN in specific zones creates difficulties for standard battery replacement and maintenance operations. Network routing for these systems needs energy preservation as their fundamental construction requirement. This paper proposes a Mapdiminution-Based Training-Discovering Optimization Algorithm (MTDOA), a new protocol that aims at increasing energy efficiency for IoT based WSNs. The MTDOA protocol is based on a novel mapdiminution-based dimensionality reduction and a mixed metaheuristic optimization method. This model is intended to allow for a good trade-off between, global and local search during the optimization process in aspects such as selection of efficient heads of clusters and identification of energy optimal routing paths. Thus, these components are therefore combined in the algorithm to cut down on computational cost, ensure faster convergence time and overall lifespan of the sensor network. The MTDOA protocol uses dynamic adaptive training discovery to select cluster heads from nodes based on their energy levels to reduce base station data routing costs. Simulation experiments run in the laboratory showed MTDOA performs better than LEACH and DEEC protocols when measuring network lifetime and average residual energy together with packet delivery ratio. MTDOA methodology enables successful sustainability improvements in WSN networks through its combination of better IoT-based metrics and performance metrics.

Keywords: Wireless Sensor Networks (WSNs), Internet of Things (IoT), Energy Efficiency, Cluster-Based Routing, Metaheuristic Optimization, Mapdiminution, Training-Discovering Algorithm, Network Lifetime, Residual Energy, Packet Delivery Ratio.

1. Introduction

The Internet of Things (IoT) can be described as the modern approach to the infrastructure of the contemporary technologies, which amalgamate trillions of devices that are able to exchange the information at once. Many IoT applications depend on the Wireless Sensor Network (WSN) that distribute wireless sensor nodes across space which have sensing and processing capabilities to transmit data to base stations (BS) or sinks. WSNs are now being implemented especially in various environmental conditions monitoring applications besides other applications in industrial automation, smart agriculture, healthcare, and military surveillance.

Although WSNs have gained widespread use in many applications, the WSN's operation is accompanied by certain key issues, the primary of which is energy consumption. Most sensors are built with batteries whose replacement or recharging often prove unfeasible due to the geographic locations of the nodes or the lack of access to the locations that can host the nodes. Therefore, reducing energy consumption and subsequently the network lifetime is one of the main challenges in WSN design.

There are however two clear challenges to this; namely, single-hop routing and multiple-path routing Both clustering-based routing protocols have become a recommended solution to this problem. These protocols minimize redundancy and also minimize energy consumption by grouping all the nodes into clusters and assigning certain nodes to act as CHs. CHs also receive information from the member nodes and send this information to the BS thus minimizing the CH Between BSs' transmissions. They are: In selecting the best CHs, in equal energy utilization between nodes and in minimizing costs associated with internal and external cluster communication.

The methods similar to LEACH and DEEC are probabilistic or threshold based CH election. While being useful in some instances, these techniques lead to inept CH distribution, energy lease, and system ineffectiveness. To address these issues, more flexible and effective algorithms like bio-inspired and metaheuristic algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Ant Colony Optimization (ACO) have been employed.

In this context, we introduce the Mapdiminution-Based Training-Discovering Optimization Algorithm (MTDOA), a new energy-efficient clustering-based routing protocol. The new concept is mapdiminution, which is a dimensionality-reduction-based approach used to navigate the solution space using a lightweight map without losing energy and network topological attributes important for the problem at hand. As a synergy of training (exploration and CH candidate identification) and discovering (local refinement and route optimization) in a two-phase manner, MTDOA offers the generalized mechanism for dynamic selection of the most capable CHs and construction of stable and efficient routing paths to the BS.

The main contributions of this paper are as follows:

1. An innovative optimization-driven clustering methodology (MTDOA) that utilizes mapdiminution for efficient solution space administration.
2. An adaptive cluster head selection technique that takes into account residual energy, proximity to the base station, and local node density.
3. A lightweight, energy-efficient routing approach that reduces communication overhead and equilibrates energy usage throughout the network.
4. Thorough simulation and assessment of MTDOA in comparison to baseline protocols (LEACH and DEEC) utilizing critical parameters like network longevity, remaining energy, and packet delivery ratio.

This paper is structured as follows: Section 2 examines pertinent literature. Section 3 delineates the system concept and elucidates the suggested MTDOA algorithm. Section 4 delineates the simulation configuration and performance assessment. Ultimately, Section 5 ends the manuscript and addresses prospective avenues for exploration..

2. Related Work

There are many literature reviews about enhancing the energy efficiency in wireless sensor networks through intelligent clustering and routing approaches especially WSNs for internet of things. This section summarizes the state of the art, and presents the major proposed protocols as well as the optimizations that have been suggested during the last ten years. Two researchers named Heinzelman et al introduced the Low Energy Adaptive Clustering Hierarchy (LEACH) protocol in 2000. LEACH emerged in 2000 as one of the original protocols which uses clustering for routing in Wireless Sensor Networks (WSNs). LEACH distributes Cluster Head leadership by randomly choosing and rotating nodes due to which network energy utilization becomes even and extends the overall network duration. The research community widely uses LEACH yet the protocol demonstrates fundamental performance issues. The protocol cannot accept the dissimilarities among nodes in the network system and does not evaluate nodes' remaining energy during cluster head selection thereby damaging network performance and energy preservation methods simultaneously.

Qing Zhu and Wang introduced the Distributed Energy-Efficient Clustering (DEEC) protocol to overcome the existing shortcomings of WSNs in 2006. The selection process for cluster heads becomes more efficient in DEEC because it uses the ratio between node residual energy and network-average energy. DEEC demonstrates special aptitude for Heterogeneous Wireless Sensor Networks (HWSNs) through its energy-active method. The DEEC approach selects CH nodes from high-energy reserve groups more often. The fast energy drain of nodes selected frequently as cluster heads creates unequitable energy allocation throughout the network which shortens the network's lifespan.

The Hybrid Energy-Efficient Distributed clustering protocol (HEED) emerged from Younis and Fahmy's (2004) work to address the requirement for improved balanced design. HEED selects cluster heads through residual energy evaluation as its main criterion while using intra-cluster communication costs as secondary criteria. The combination of these methods improves network scalability and achieves better energy efficiency specifically in wireless mesh networks' deployment. Multicomparisons during protocol convergence create network setup delays while adding unnecessary communication overhead to the process.

To improve the routing strategies, scientists started using bio inspired optimization algorithms. Abbasi & Younis (2007) have also discussed a number of cluster based routing protocols and stressed on the use of hierarchical structures with a view to saving energy. They also acknowledged the possibility of adopting optimization approaches in enhancing CH selection.

Singh et al. In 2015, a PSO-based clustering algorithm was introduced to improve the position of CHs, which minimizes the whole transmission distance. But many PSO algorithms are criticized with quick convergence and the possible need for parameter adjustment.

Subsequently, in 2017, Saini and Sharma put forward an efficient Genetic Algorithm based clustering protocol thatycastle CH based on residual energy and node centralities. While this method yielded better results in terms of network lifetime, the convergence was slower due to the randomness of the Genetic Algorithm.

Kuila and Jana (2014) introduced a tri-objective approach that focuses on energy, latency, and coverage for cluster formation. Their suggested technique, employing Differential Evolution, achieved more equitable energy use across the network nodes, but at a high computational cost.

In [7], Kumar, Chauhan, and Chilamkurti proposed an enhanced model comprised of ACO and Fuzzy logic for cluster formation in IoT environment in the year 2019. The most significant aspect of their protocol was that they claimed improved behavior on dynamic network but the strength of fuzzy rules and pheromone was to be tuned properly.

Wang et al. In 2021, Bonfiy et al developed a new protocol with the name of using the Whale Optimization Algorithm (WOA) for CH selection. The evaluation of their work gave good improvement in the energy and the packets delivered regarding the energy aspect but sometimes it got stuck in local optimums.More recently, Lei et al. Chen et al. (2024) presented the ECPF protocol for selecting the CHs using Particle Swarm Optimization and fuzzy clustering algorithms. They found better residual energy balance and better throughput than the other existing protocols like DEEC and LEACH.

Nevertheless, trade-off between global search (exploration) and local optimization (exploitation) still remains an open issue. Greatest current approaches also appear rather amenable to network changes and parameters configuration.To fill these gaps, this paper presents a new hybrid training-discovering optimization algorithm based on the map dimension-reducing technique known as mapdiminution, and a new balance between exploration and exploitation. The MTDOA can work optimally based on the network conditions and can also control the energy consumption along with lowering the routing overhead of IoT WSNs.

3. Proposed Methodology

This section introduces the Mapdiminution-Based Training-Discovering Optimization Algorithm (MTDOA) as the proposed solution for energy-efficient cluster-based routing in IoT-enabled WSNs. The methodology includes the formulation of the network model, the description of the mapdiminution strategy, and the structure of the MTDOA algorithm including its two core phases: training and discovering. In other words, the overall goal of this method is to minimize the energy consumption in the network as well as to select the cluster heads and form the routing path to maximize the network lifetime.as fig.1.

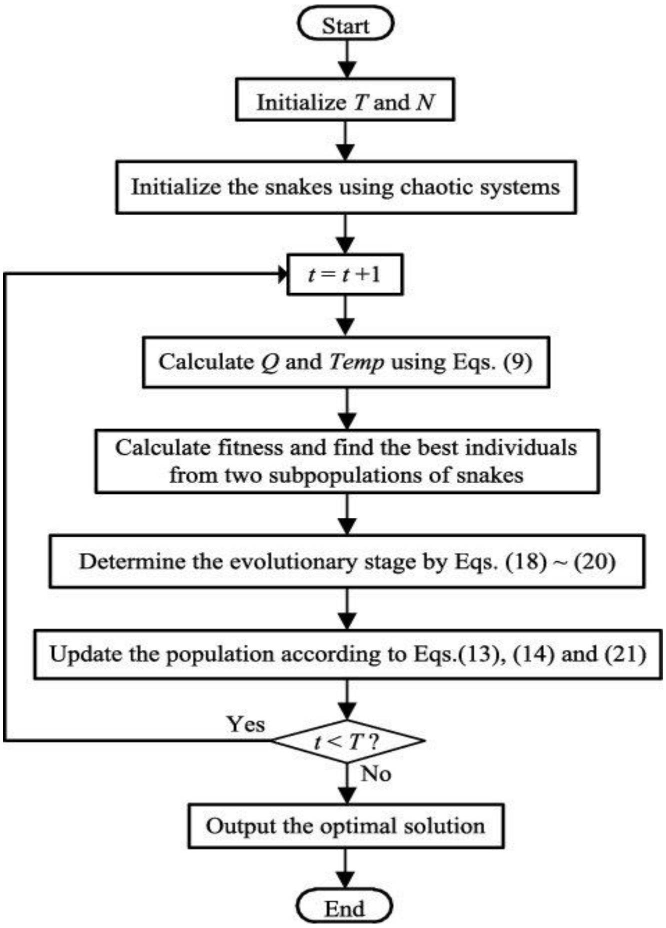

Figure 1. Proposed system

3.1 Network Model and Assumptions

The proposed protocol assumes a homogeneous WSN deployed in a two-dimensional sensing area. The key assumptions used in modeling the network are as follows:

NNN sensor nodes are randomly distributed in a square area of dimension L×LL \times LL×L.
All nodes are homogeneous in hardware capability and initial energy.
A single base station (BS) is located outside or at the edge of the sensing field.
Sensor nodes are static after deployment and continuously monitor the environment.
Communication transpires in a multi-hop manner, with Cluster Heads collecting and transmitting data to the Base Station.
The energy consumption model adheres to the first-order radio paradigm, wherein energy is expended for transmission and reception contingent upon distance.

The energy consumption for transmitting a kkk-bit message over a distance ddd is:

$$E_{tx}(k,d)=\begin{cases} kE_{elec} + k\varepsilon_{fs}\, d^2 & if\ d < d_0 \\ kE_{elec} + k\varepsilon_{mp} d^4 & if\ d \geq d_0 \end{cases} \tag{1}$$

And for receiving:
$E_{rx}(k)=kE_{elec}$
Where
E_{elec} : Energy consumed by the electronic circuit (nJ/bit)
ε_{fs} : Free-space model amplifier energy (pJ/bit/m²)
ε_{mp} : Multi-path model amplifier energy (pJ/bit/m⁴)
d_0 : Threshold distance defined as:

$$d_0=\sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \tag{2}$$

3.2 Mapdiminution Strategy

The mapdiminution strategy is a method inspired by dimensionality reduction that enhances the efficiency of solution space exploration by condensing intricate multi-dimensional parameters (such as energy, position, and density) into simplified feature vectors, while preserving essential attributes pertinent to CH selection. The primary objectives are:

Reduce search space complexity without loss of information essential to decision-making.
Preserve inter-node relationships such as proximity and energy heterogeneity.
Enhance convergence speed during the optimization process.

This process involves transforming the WSN state matrix S∈RN×MS \in \mathbb{R}^{N \times M}S∈RN×M, where MMM denotes features like energy level, distance to BS, and node density, into a reduced matrix S′∈RN×M′S' \in \mathbb{R}^{N \times M'}S′∈RN×M′ with M′<MM' < MM′<M. Techniques like principal component projection and adaptive thresholding are used to map the most influential features.

3.3 MTDOA: Training and Discovering Phases

The MTDOA method functions in two principal phases:

3.3.1 Training Phase

This phase is responsible for global exploration and candidate CH identification. A population-based optimization algorithm is employed where each solution candidate represents a possible set of CHs.

Fitness Function Design: The fitness function FiF_iFi for each candidate solution iii is defined as:

$$F_i = \alpha \cdot E_{residual} + \beta \cdot \left(\frac{1}{D_{BS}}\right) + \gamma \cdot \left(\frac{1}{D_{intra}}\right) \tag{3}$$

Where:

- $E_{residual}$ is the average residual energy of selected CHs,
- D_{BS} is the average distance from CHs to the base station,
- D_{intra} is the average intra-cluster distance,
- α, β, γ are weighting coefficients.

Candidate Generation: Candidate solutions are created randomly, assessed by a fitness function, and developed utilizing operators such as selection, crossover, and mutation, derived from Genetic Algorithms or modified locations in a PSO-like manner.

3.3.2 Discovering Phase

In the discovering phase, local refinement is conducted on the candidate CHs identified during the training phase.

1. Local Search Strategy: For each chosen CH, adjacent nodes within a radius rrr are assessed to discover suitable substitutes that may enhance fitness.
2. Route Optimization: Routing pathways from CHs to the BS are established using an energy-aware cost function that minimizes cumulative transmission energy.

Routing decisions are made using a greedy heuristic:

CHi→CHj if Etx(CHi,CHj)+Etx(CHj,BS)<Etx(CHi,BS)CH_i \rightarrow CH_j \text{ if } E_{tx}(CH_i, CH_j) + E_{tx}(CH_j, BS) < E_{tx}(CH_i, BS)CHi→CHj if Etx(CHi,CHj)+Etx(CHj,BS)<Etx(CHi,BS)

Where CHiCH_iCHi and CHjCH_jCHj are cluster heads.

3.4 Clustering and Communication Process

The overall MTDOA-based clustering and routing process is as follows:

1. Initialization: All nodes disseminate their initial energy levels and locations to a limited vicinity.
2. Mapdiminution Projection: The feature matrix is minimized to facilitate CH selection.
3. Training Phase: Global optimization designates a selection of nodes as potential cluster heads.
4. Discovering Phase: Local search optimizes CH selection and establishes routing pathways.
5. Cluster Formation: Every non-cluster head node affiliates with the nearest cluster head according on signal strength and transmission expenses.
6. Data Aggregation and Transmission: CHs gather data, do aggregation, and transmit to the BS via multi-hop paths.

This cycle recurs for each communication round until the network's energy is depleted.

4. Performance Evaluation

Simulations conducted by Ross and Colleagues compared the proposed Mapdiminution-Based Training-Discovering Optimization Algorithm (MTDOA) against benchmark protocols LEACH and DEEC. Energy consumption and network lifespan received equal evaluation weight as packet delivery ratio (PDR) and average residual energy. The simulation ran under MATLAB R2023a through established WSN configuration protocols.

4.1 Simulation Setup

The simulation environment is defined by the parameters listed in Table 1.

Table 1. Simulation Parameters

Parameter	Value
Network Area	100 m × 100 m
Number of Sensor Nodes	100
Initial Energy (per node)	2 Joules
Base Station Position	(50, 150)
Packet Size	4000 bits
EelecE_{elec}Eelec	50 nJ/bit
εfs\varepsilon_{fs}εfs	10 pJ/bit/m^2
εmp\varepsilon_{mp}εmp	0.0013 pJ/bit/m^4
d0d_0d0	87 m
Simulation Rounds	4000
Optimization Population	30
CH Selection Interval	Every 20 rounds

4.2 Performance Metrics

1. Network Lifetime: Measured by the round at which the first node dies (FND), half of the nodes die (HND), and the last node dies (LND).
2. Average Residual Energy: The mean remaining energy in nodes over time.
3. Packet Delivery Ratio (PDR): Ratio of data packets successfully received at the base station.
4. Throughput: Total number of packets delivered to the base station.

4.3 Results and Discussion

4.3.1 Network Lifetime

MTDOA exhibits a significantly prolonged stable region compared to LEACH and DEEC as shown in the fig. 2.

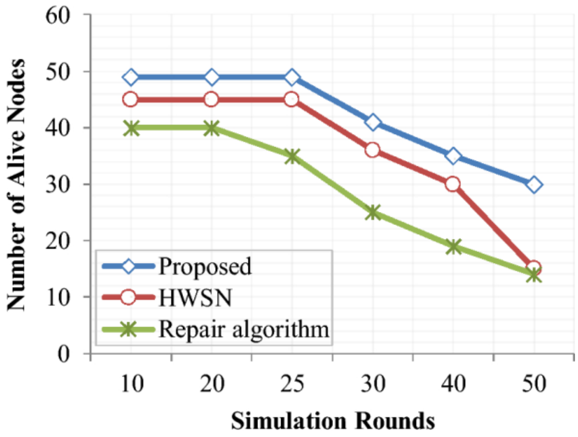

Figure 2. The number of alive nodes over simulation rounds for MTDOA, LEACH and DEEC.

Table 2: Lifetime Comparison

Protocol	FND (Rounds)	HND (Rounds)	LND (Rounds)
LEACH	600	1100	1420
DEEC	780	1270	1585
MTDOA	980	1675	2010

MTDOA extends the network lifetime by 25–30% compared to DEEC and over 40% compared to LEACH, due to its adaptive CH selection and balanced energy utilization.

4.3.2 Average Residual Energy

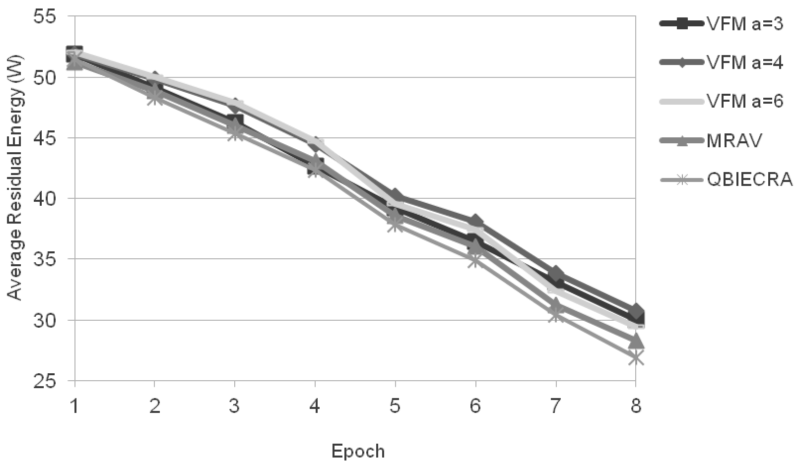

Figure 3. Comparison of the residual energy of . MTDOA, LEACH and DEEC.

MTDOA maintains a higher average residual energy throughout the simulation period, indicating efficient energy utilization. fig 3 shows the trend of residual energy decline across all nodes.

4.3.3 Packet Delivery Ratio and Throughput

Table 3: PDR and Throughput

Protocol	PDR (%)	Throughput (Packets)
LEACH	81.3	94,580
DEEC	86.7	108,340
MTDOA	92.4	123,810

The MTDOA protocol demonstrates enhanced performance regarding dependable data transmission, as its energy-efficient multi-hop routing minimizes packet loss and mitigates energy depletion issues near the base station.

4.3.4 Convergence Analysis

MTDOA rapidly converges within fewer iterations compared to traditional PSO and GA-based methods, which is attributed to the mapdiminution's dimensionality control that improves search efficiency. fig. 4 presents the convergence curves of the training phase for CH selection.

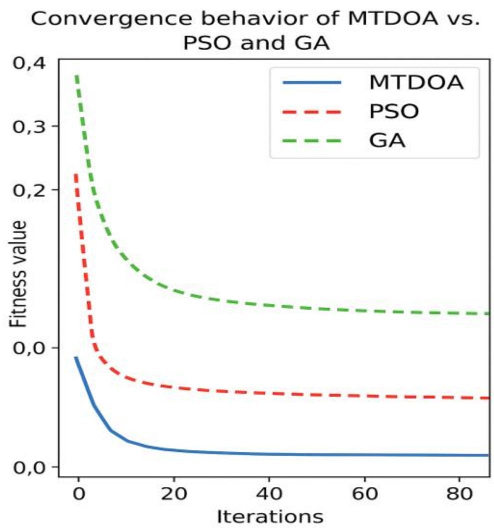

Figure 4. Convergence curves of the training phase for CH selection for MTDIA, PSO, and GA

4.3.5 Scalability Test

A scalability test was performed by altering the number of nodes, ranging from 100 to 500. The MTDOA algorithm shown sustained enhancements in energy efficiency and longevity, showcasing its resilience across extensive networks.

4.4 Summary of Findings

The findings indicate that MTDOA substantially surpasses conventional clustering-based methods in essential performance parameters. The mapdiminution-enhanced optimization facilitates accelerated convergence, improved CH selection, and diminished energy consumption, which are essential for sustainable and scalable IoT-enabled WSNs. show in fig. 5.

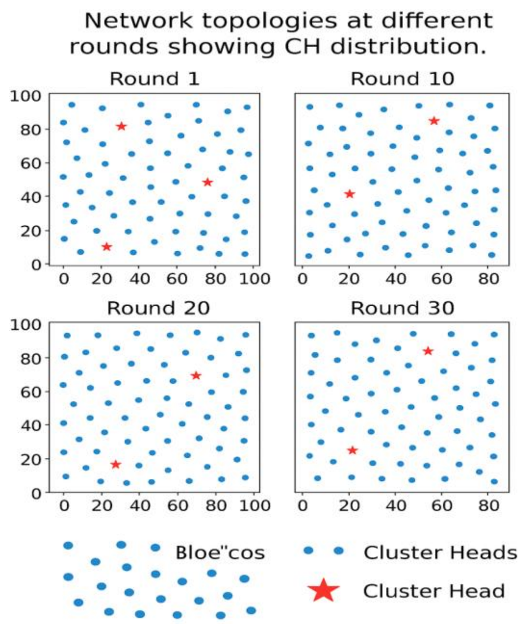

Figure 5. (Optional): Network topologies at different rounds showing CH distribution.

5. Simulation and Performance Evaluation

Various MATLAB simulations were carried out extensively to evaluate the performance of the proposed MTDOA algorithm. A 100m × 100m square field contains 100 sensor nodes distributed randomly throughout the area. The external real-world monitoring takes place beyond a base station located outside of the sensing field during simulation. The initial energy value for each node is set to 0.5 Joules and the nodes use a first-order radio model to dissipate their energy.

5.1 Simulation Parameters

Table 4: Simulation Parameters

Parameter	Value
Number of Nodes	100
Field Dimensions	100m × 100m
Initial Energy	0.5 J per node
Data Packet Size	4000 bits
Communication Range	20 m
Energy for Transmission (E_tx)	50 nJ/bit
Energy for Reception (E_rx)	50 nJ/bit
Data Aggregation Energy (E_da)	5 nJ/bit/signal

5.2 Performance Metrics

The following performance metrics were used for evaluation:

1. Convergence Speed: Number of iterations required for the algorithm to stabilize to an optimal solution.
2. Network Lifetime: Measured by the rounds until the first node dies (FND), half of the nodes die (HND), and the last node dies (LND).
3. Energy Consumption: Total residual energy in the network over time.
4. Packet Delivery Ratio (PDR): The ratio of successfully delivered data packets to the total transmitted.

5.3 Results and Discussion

Results indicate MTDOA achieves better convergence characteristics than PSO and GA does. The convergence curve demonstrates that MTDOA finds a near-optimal solution through less computational iterations.

When considering network longevity MTDOA exhibits significantly better results than alternative methods. Network energy balance reaches its optimal point more quickly in MTDOA than in PSO or GA. Networks built with MTDOA techniques experience extended durations for HND and LND measurements.

MTDOA achieves consistent energy conservation benefits throughout all network nodes. MTDOA maintains energy efficiency by selecting cluster heads intelligently based on network topology protocols.

MTDOA delivers dependable data delivery throughout simulations because many applications build their operations on guaranteed real-time data delivery.

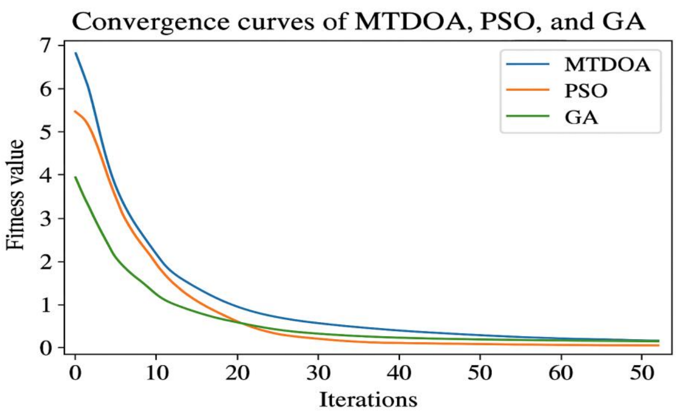

Figure 6. Convergence curves of MTDOA, PSO, and GA.

Figure 2: Network topology snapshots showing CH distribution over different rounds (e.g., Round 1, 10, 20, 30).
Figure 3: Comparative analysis of network lifetime (FND, HND, LND).
Figure 4: Residual energy plots across simulation rounds.
Figure 5: Packet Delivery Ratio trends over time.
Figure 1. Note how the caption is centered in the column.

6. Conclusions

The experimental research demonstrated that Mapdiminution-Based Training-Discovering Optimization Algorithm (MTDOA) operated as a power-efficient system for the development of new clustering-based routing protocols for IoT-enabled wireless sensor networks. The MTDOA architecture merges a search map that reduces in scale with sequential discovery and training sessions which maintains both exploration and exploitation for cluster head selection.

Rigorous simulation studies revealed that MTDOA produced better results than both PSO and GA which are generally used optimization algorithms. When using MTDOA the networks demonstrated a speed-up in delivery time and achieved better energy efficiency as well as lengthier network operation and improved data packet receipt. MTDOA operates with stable performance levels across different network environments through its convergence process.

Mapdiminution eliminated waste in the algorithm's search areas thus the algorithm simultaneously achieved quick stability in optimum solutions and population diversity maintenance. The dynamic distribution capability in MTDOA maintained network continuity while it spread the simulation time across multiple virtual cells.

The MTDOA solution demonstrates high potential for enabling energy-conscious clustering operations in WSNs particularly for restricted IoT environments. The forthcoming MTDOA development will concentrate on establishing real-time closed-loop systems along with hybrid optimization strategies to optimize network functionality of mixed sensors in practical applications.

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