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Multi-Objective Genetic Algorithm-Based Clustering for Energy Distribution and Lifetime Maximization in Wireless Sensor Networks

A. Aliabadian [1,*]

[1] Assistant Professor, Department of Electrical and Biomedical Engineering, Shomal University, Amol, Iran

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ABSTRACT

Wireless Sensor Networks (WSNs) consist of numerous resource-constrained sensor nodes that collaboratively monitor physical or environmental conditions and transmit the collected data to a base station. Due to the limited battery capacity of sensor nodes, energy efficiency remains one of the most critical challenges affecting network lifetime and overall performance. Clustering has been widely adopted as an effective approach for reducing communication overhead, balancing energy consumption, and improving network scalability. However, traditional clustering protocols such as LEACH often suffer from inefficient cluster-head selection and uneven energy distribution among sensor nodes. To address these limitations, this paper proposes a clustering methodology based on a Multi-Objective Genetic Algorithm (MOGA) that simultaneously optimizes cluster-head selection, intra-cluster communication distance, and energy utilization. The proposed approach aims to achieve balanced energy consumption while extending network lifetime and maintaining communication reliability. Extensive simulations were conducted and the obtained results were compared with conventional clustering techniques. Performance evaluation demonstrates that the proposed method significantly reduces energy consumption, improves cluster stability, and increases overall network efficiency. The results indicate that the proposed optimization framework provides a robust and effective solution for energy-aware clustering in WSN environments.

1. INTRODUCTION

Clustering in wireless sensor networks (WSNs) is one of the pivotal techniques for efficient network management. In this approach, sensor nodes are partitioned into groups called clusters, where each cluster is managed by a designated Cluster Head (CH). The CH is responsible for aggregating data from its member nodes and transmitting the consolidated data to the Base Station (BS). This hierarchical topology drastically reduces the number of direct transmissions to the base station, thereby significantly curtailing the total energy consumption of the network. Furthermore, clustering mitigates data traffic congestion, suppresses communication interference, and enhances overall network reliability [1-3].

[*] Corresponding Author: a.aliabadian@shomal.ac.ir
Assistant Professor, Department of Electrical and Biomedical Engineering, Shomal University, Amol, Iran

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The significance of clustering is magnified due to the severe energy constraints of sensor nodes. These nodes typically operate on small, irreplaceable batteries and are frequently deployed in harsh, inaccessible environments. Consequently, designing a network framework capable of distributing energy consumption uniformly among nodes thereby preventing the premature death of critical nodes is of paramount importance. Beyond extending the network lifetime, clustering can substantially improve the network's Quality of Service (QoS), ensuring that data packets are delivered to the base station reliably and with minimal latency [4-6].

The applications of clustering in wireless sensor networks are highly broad and diverse. These networks are extensively deployed in environmental monitoring for forest fire detection, water resource management, air quality tracking, and natural disaster control. In military and defense domains, clustering enables tactical tracking and threat detection with low power consumption. Moreover, in smart industries, automated hospitals, and digital healthcare networks, clustering facilitates the efficient management of sensory data streams, thereby optimizing the performance of intelligent monitoring frameworks.

Despite its inherent benefits, clustering introduces several architectural challenges. Selecting optimal cluster heads, ensuring balanced energy distribution, managing node mobility, enhancing network scalability, and minimizing end-to-end delay are among the most critical issues. Additionally, dynamic environmental changes, energy fluctuations, and the high probability of node failures complicate the design of effective clustering algorithms. Consequently, conventional, localized algorithms often fail to maintain efficiency under dynamic conditions, highlighting the need for more intelligent, global optimization approaches [7-10].

To address these challenges, methodologies based on intelligent metaheuristics and multi-objective optimization algorithms have been developed. The Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and other evolutionary computation frameworks navigate the complex response space intelligently. These paradigms facilitate the optimal selection of cluster heads, promote balanced load distribution, and minimize the net energy consumption of the network. Deploying these advanced techniques significantly extends network longevity, curtails communication delays, enhances reliability, and boosts data transmission quality, providing researchers with highly efficient tools for designing next-generation sensor networks.

Here is the professional, publication-ready English translation of Sections 2 and 3, incorporating standard technical terminology used in IEEE, ACM, and Elsevier journals specializing in wireless ad-hoc and sensor networks.

2. EXISTING METHODS

Network lifetime and coverage are fundamental parameters in the structural design of wireless sensor networks. In a WSN, sensor nodes and the sink node are spatially distributed to ensure sufficient coverage across the target area. However, long-range communication between nodes leads to excessive energy depletion and curtails the network lifetime. In study [5], an Evolutionary Algorithm (EA)-based methodology is introduced to address this optimization problem. Empirical results demonstrate that this algorithm is capable of discovering superior solutions compared to conventional EAs.

In wireless sensor networks, sensor nodes and the central sink are positioned at a distance from one another to provide adequate spatial coverage. However, the communication distance between nodes is directly correlated with energy dissipation, and this transmission range is fundamentally constrained. To address this issue, a clustering framework coupled with an inter-cluster multi-hop routing algorithm is deployed to guarantee adequate coverage, load balancing, and network lifetime enhancement. In paper [6], a Negotiable Evolutionary Algorithm (NEA) is implemented to resolve the multi-objective optimization problem in WSNs. Simulation profiles verify that the NEA stands as a highly effective approach.

Maximizing the lifetime of wireless sensor networks is an essential research problem, as the vast majority of sensor nodes in these networks are characterized by highly constrained battery capacity; thus, the energy consumption of each individual sensor must be minimized. The node density in a WSN can seamlessly scale up to tens of thousands of devices. Paper [7] presents a quantum-inspired evolutionary algorithm designed to enhance the performance of the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol. Experimental results indicate that the proposed algorithm outperforms the standard LEACH protocol by 12% in terms of energy dissipation reduction.

Low-power energy-efficient clustering in wireless sensor networks (WSNs) has attracted significant research attention over the past few decades. In these network topologies, Cluster Heads (CHs) shoulder severe overhead burdens, including data sensing, data aggregation, and transmission to the base station. Suboptimal cluster formation can lead to an excessive load on specific CHs, accelerating their energy depletion. Paper [8] proposes a load-balanced clustering algorithm based on the Genetic Algorithm (GA) to improve network longevity and optimize energy utilization.

For wireless sensor networks deployed across critical domains such as military, medical, meteorological, and geological frameworks reliable communication and efficient routing mechanics are imperative. In paper [10], the performance of the Artificial Bee Colony (ABC) algorithm in WSN routing operations is investigated. The resulting performance metrics confirm that the deployed routing protocol successfully extends the network lifetime through strategic energy conservation. A structural complexity analysis of the cluster-based routing strategy was conducted using the ABC algorithm. The operational results and computational analyses verify that the ABC algorithm offers promising solutions for wireless sensor network routing.

The primary objective in the design and operation of wireless sensor networks is the maximization of network lifetime, which fundamentally relies on network connectivity. Network connectivity is directly dependent on the battery lifespan of individual sensor nodes. However, these nodes possess highly restricted energy resources, and battery replenishment or replacement is extremely difficult or altogether impractical. Therefore, to extend the operational lifetime of sensor networks, energy must be conserved efficiently, which is achievable through energy-optimized routing algorithms. Hierarchical cluster-based routing algorithms can significantly decrease energy demands; however, the core problem and primary challenge in cluster formation lies in selecting appropriate cluster heads while simultaneously considering multiple diverse parameters such as the residual energy of the nodes, neighbor node density, node position, and distance to the base station. Optimal cluster formation is a well-known Non-deterministic Polynomial-time hard (NP-hard) problem. To design an energy-optimal cluster topology aimed at extending the network lifetime, evolutionary-based techniques are deployed, which also guarantee energy-optimized routing paths for the sensor nodes [11].

A wireless sensor network represents an interconnection of wireless nodes with highly restricted energy and memory capacities. These networks can be deployed across numerous critical applications, including military operations, search and rescue management, wildfire detection, and other scenarios. In a flat routing architecture, every node assumes an identical dual role as both a sensor and a router. Due to the mobile nature of nodes in certain wireless sensor networks, the network topology can fluctuate frequently. Maintaining a dynamic topology can result in substantial control message overhead. To prevent the message overhead associated with topology maintenance, paper [12] introduces a cluster-based mobile wireless sensor network optimized using the Meme algorithm. In this network paradigm, nodes are initially partitioned into clusters, and the designated cluster heads route the consolidated data packets to the base station. The validation of the network framework was executed through extensive simulation studies. The results demonstrate that this proposed technique yields superior performance compared to existing state-of-the-art techniques.

3. PROPOSED METHODOLOGY

The NSGA-II (Non-dominated Sorting Genetic Algorithm II) [1] is one of the most prominent algorithms for solving multi-objective optimization problems where multiple objective functions are optimized simultaneously. Developed by Kalyanmoy Deb et al. in 2002, NSGA-II stands as one of the most widely applied multi-objective optimization algorithms globally. It has gained widespread popularity due to its high computational efficiency, relative simplicity, and exceptional capability in preserving population diversity. The foundational concepts of NSGA-II are outlined below [13-16]:

Pareto Front: A set of mathematically optimal solutions where none of the choices dominate one another. In other words, improving one objective function necessarily results in the degradation of another objective.

Non-dominated: A candidate solution is classified as non-dominated when there exists no alternative solution within the current population that yields superior performance across all objective functions simultaneously.

Non-dominated Sorting: Candidate solutions are systematically stratified and sorted based on their level of non-dominance. The first front (rank 1) comprises solutions that are not dominated by any other solution in the population. The second front comprises solutions that are dominated strictly by individuals in the first front, and this sorting hierarchy continues recursively.

The operational steps of the NSGA-II algorithm are detailed below:

Initial Population Generation: The algorithm initiates by randomly generating an initial population of candidate solutions.

Population Evaluation: Each individual within the population is quantitatively **evaluated** using the predefined objective functions.

Non-dominated Sorting: The population is stratified based on non-dominance levels, and a specific rank is assigned to each individual. Individuals assigned to the first front possess the highest priority rank.

Crowding Distance Calculation: To preserve structural diversity among individuals sharing identical Pareto ranks, a neighborhood crowding distance metric is computed. This distance quantifies how isolated or distinct an individual is relative to its neighbors in the objective space.

Selection: While conventional evolutionary selection techniques like roulette wheel or tournament selection can be used, NSGA-II leverages a crowded-comparison operator based on a combination of Pareto rank and crowding distance to select individuals for generating the subsequent generation.

Crossover and Mutation: The selected parent individuals undergo genetic crossover and mutation operators to produce new offspring.

Next-Generation Population Assembly: The parent population and the newly generated offspring population are merged into a combined pool, which is subsequently sorted up to the original population size to construct the next generation. This merging and selection process guarantees elitism, preserving the best historical solutions while maintaining population diversity.

Iterative Termination: These sequential steps are repeated iteratively until a predefined termination criterion such as a maximum generation count or reaching a specific target threshold is fully satisfied.

The operational phases for cluster formation using the Multi-Objective Genetic Algorithm (MOGA) are structured as follows:

Initial Population Generation: The algorithm begins by generating an initial population of chromosomes, where each chromosome represents a potential network configuration of Cluster Heads (CHs) and non-CH (member) nodes. Each chromosome encodes spatial data regarding node coordinates, residual energy status, and other critical network metrics.

Fitness Evaluation: The fitness function is mathematically calculated for each individual chromosome. In a multi-objective optimization scenario, the genetic algorithm must concurrently evaluate multiple conflicting metrics, such as minimizing net energy consumption, maximizing network lifetime, and optimizing spatial coverage. These objectives are typically evaluated using weighted-sum techniques or non-dominated ranking paradigms like the NSGA-II algorithm.

Selection: To engineer the subsequent generation, the algorithm isolates and selects chromosomes exhibiting higher fitness values. In multi-objective evolutionary algorithms, selection operators such as tournament selection or dominance-based rank selection are utilized.

Crossover and Mutation: Crossover and mutation operators are applied to introduce structural variations within the chromosomes, preserving population diversity and increasing the probability of escaping local optima to discover superior global solutions.

Offspring Fitness Evaluation: Following the application of genetic crossover and mutation operators, the newly generated offspring chromosomes are re-evaluated, and their objective fitness vectors are calculated.

Algorithm Termination: The evolutionary loop executes continuously until it encounters a specific termination threshold, such as reaching the maximum iteration ceiling or converging upon an acceptable Pareto-optimal configuration.

The principal advantages of deploying a Multi-Objective Genetic Algorithm (MOGA) for WSN clustering include:

Simultaneous Multi-Objective Optimization: It provides the mathematical capacity to analyze and optimize disparate network metrics concurrently, such as decreasing energy dissipation while improving cluster load balancing.

Discovery of Pareto-Optimal Solutions: Multi-objective evolutionary algorithms can generate an entire front of Pareto-optimal trade-offs, each presenting distinct architectural advantages and trade-offs tailored to specific deployment needs.

Network Lifetime Enhancement: By carefully factoring in heterogeneous node characteristics and residual CH energy profiles, MOGA significantly bolsters network longevity and global data-routing efficiency.

4. SIMULATION RESULTS

The proposed methodology and the existing comparative techniques were implemented within the MATLAB environment developed by MathWorks. The hardware testbed featured an Intel(R) Core™ i5-4460 CPU @ 3.2 GHz processor equipped with 16 GB of RAM.

It is worth noting that a wireless sensor network incorporates several key variables defined within the MATLAB software. These parameters include the total node count, the target cluster head (CH) percentage, network area dimensions, path loss exponent, maximum round/iteration limits, base station coordinates, and the initial battery energy allocation. In the MATLAB programming environment, these operational parameters are initialized to facilitate high-fidelity simulation of network performance and robust evaluation of diverse clustering algorithms.

The genetic optimization parameters for the simulation were configured as follows: a maximum iteration limit of 100, a population size of 100, a crossover probability of 0.5, and a mutation probability of 0.5. The mutation rate was also held at 0.5. Figure 1 illustrates an exemplary network topology containing 200 nodes, where the distributed sensor nodes are designated in blue. In this specific scenario, the initial target CH fraction parameter was initialized to 0.02. Figure 2 depicts a representative output of the cluster formation process, where member nodes are mapped to their respective designated CHs via red communication links. Figure 3 delineates the dynamic fluctuation in the percentage of alive nodes across successive iterations.

The network lifetime curve benchmarking the proposed framework against alternative state-of-the-art routing protocols is plotted in Figure 4. The paramount architectural advantage of the proposed methodology compared to baseline protocols lies in the optimal determination of cluster centers driven by the multi-objective genetic algorithm. Under this approach, the evolutionary parameters are seamlessly adjusted to significantly bolster the precision of the routing results.

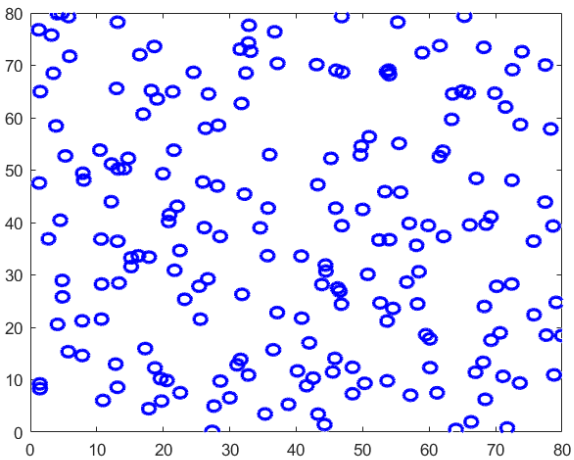

Fig. 1. Topological distribution of sensor nodes.

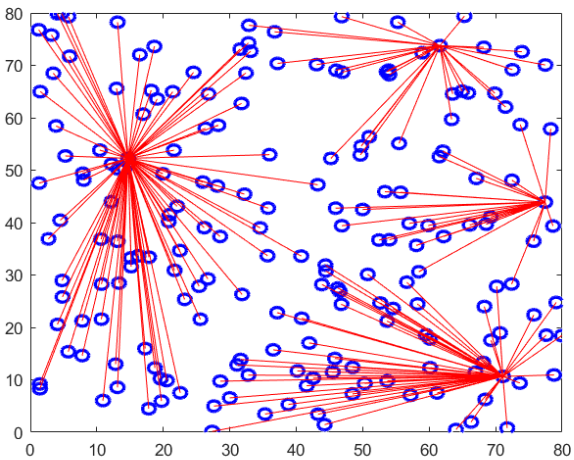

Fig. 2. Cluster formation and node connection configuration.

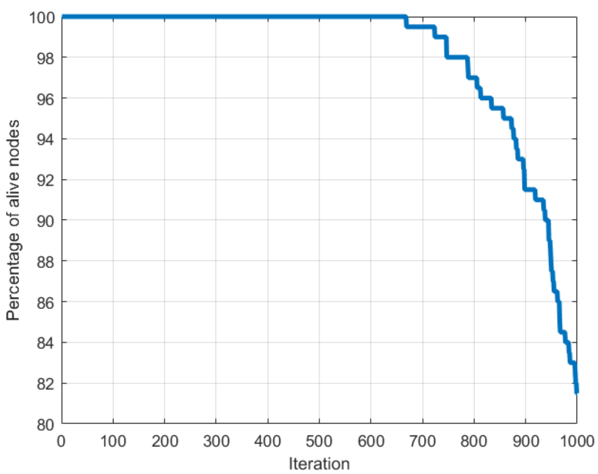

Fig. 3. Percentage of alive nodes as a function of iteration/round count.

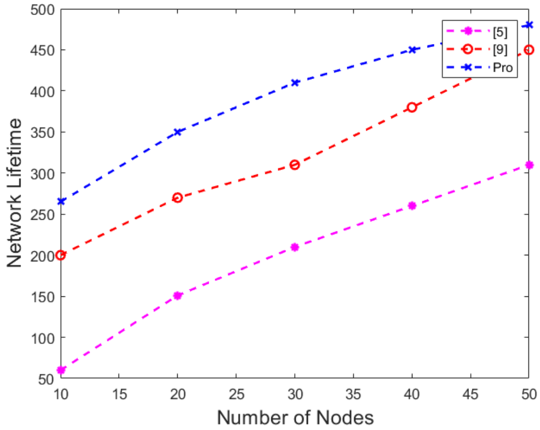

Fig. 4. Comparative network lifetime analysis between the proposed method and alternative state-of-the-art approaches.

5. CONCLUSION

In this research, a novel clustering framework for wireless sensor networks is presented, leveraging a hybrid paradigm that integrates a Multi-Objective Genetic Algorithm (MOGA) with the K-means clustering technique. Defining optimal cluster centers constitutes a critical bottleneck in sensor network clustering, as their spatial distribution directly commands net network routing efficiency. To address this limitation, a multi-objective genetic algorithm was deployed to globally optimize the spatial localization of cluster heads. Within this proposed hybrid execution, the multi-objective genetic algorithm is mathematically engineered to tune the operational parameters of the K-means algorithm, thereby dramatically enhancing overall cluster definition and accuracy.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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