Journal of Intelligent Systems and Internet of Things
Vol. 14, No. 02, PP. 36-43, 2025
DOI: https://doi.org/10.54216/JISIoT.140204

Reduce Energy Consumption and Increase Lifetime via Genetic Algorithm over Wireless Communication Networks

Mohammed Arif Nadhom Obaid Al-agar[1,*], , Zaynab Saeed Hameed[1] , Israa Ali Al-Neami[1]
Sergey Drominko[2], Erina Kovachiskaya[2]

[1]Department of Computer Engineering, University of Technology, Baghdad, Iraq

[2]Faculty of Information Technology and Robotics, Vitebsk State Technological University, Belarus

Emails: MohammedArif.N.Alagar@uotechnology.edu.iq; zaynab.s.hameed@uotechnology.edu.iq; Israa.A.AlShaikhli@uotechnology.edu.iq; Serdrominko1996@vsu.by; EriKovachi98rus@vsu.by

Abstract

Wireless sensor networks have been identified as one of the most important technologies. A vast amount of research and development has been devoted to this area in the past decade. Nowadays, they have been applied in various fields including environment monitoring, smart building, medical care, and etc. With the advances in electronics, wireless communications, and sensor technology, more and more new opportunities have been created for the research in wireless sensor networks. However, the successful implementation of WSN faces many challenges, such as limited power, limited memory, and limited computing capability. Among them, limited power is the most critical restriction because it is usually impossible for the battery-powered sensor nodes to be recharged. Therefore, one of the main areas of interest for wireless sensor network research is how to reduce power consumption. The proposed system classifies sensor nodes into two operational modes, optimizes node deployment, and finds optimal node placements using a genetic algorithm (GA) to minimize the energy consumption of the WSN. The system's successful testing on a simulated WSN meant for radiation site identification revealed its potential for practical real-world applications.

Received: March 08, 2024 Revised: June 14, 2024 Accepted: October 05, 2024

Keywords: Power Consumption; Genetic Algorithm (GA); Battery-Powered Sensors; Energy Efficiency

1. Introduction

Wireless sensor network consists of individual sensors that monitor and record the physical conditions before sending the collected information to a designated destination. WSNs can measure many environmental factors, such as pollution levels, humidity, temperature, wind and sound. Such sensors have a broad range of applications, such as forest hearth prediction, chemical and fuel leak threat detection, weather forecasting, earthquake and tsunami detection, water quality control, site visitor tracking and volcanoes [1]. High-potential technologies like WSN are employed in a variety of industries, including agriculture, security, resources union, transportation, health and military [2]. Another essential element of IoT technology is WSN [3]. In wireless sensor networks (WSNs), an enormous amount of sensors can wirelessly communicate across short distances with minimal power consumption. Many distinct sensors are used to build systems since a single sensor node's capacity to collect data is dependent upon its domain programming. The WSN is composed of a few cluster heads. The cluster heads exchange data with the ships and base station as well as obtain information from external sensors with a range of either high or low sensors[4]. WSN dispersal randomly placed sensor nodes were installed around the field to monitor and detect program usage. Since a significant quantity of electricity is used for data transmission, energy efficiency is the primary objective in WSN. As a result, methods to choose the optimal path must be followed for effective energy intake[5]. The requirement to function within stringent power constraints presents a major barrier in the design and deployment of wireless sensor networks (WSNs). Distributed, independent sensor nodes make up WSNs; these nodes track environmental conditions and send data to a central processing hub [6].

In order to meet quality of service (QoS) requirements for departed clients with certain real-time applications in terms of latency, jitter, throughput, and bandwidth, routing determines the most efficient path from the supply station to the vacation site[7]. Different routing methods, including genetic algorithm (GA), were utilized in Wi-Fi networks, which mostly use hierarchical optimum routing [5]. In order to ascertain the power availability of the sensor devices that contribute to the community's longevity, GA's advanced routing demonstrated strong overall performance. Moreover, maintaining the highest quality of WSN services is a multi-objective challenge that involves continuously treating the consistency for every decisions, including network lifetime, efficiency, latency and coverage energy[8].

2. Related Works

The author in [9] have demonstrated an energy-efficient cluster-based routing protocol for WSN that makes use of the ant colony and butterfly optimization algorithms. Nevertheless, it takes a lot longer to complete a task in a wireless sensor networks data computing nodes than it does to transfer data to a transferring node. [10] Focuses on wireless sensor networks (WSNs) energy-efficient routing strategies. WSN has idle periods for a variety of reasons, including as time-varying sensor monitoring mandated by the process. In some WSN applications, good efficiency is expected to suit industry needs. [11] Presented a novel capacity constraint-aware method that lessens unreliability caused by the instability and low efficiency of temperature-aware strategies. To maintain performance, academics developed a paradigm for the same purpose. Integrated devices are increasingly using FPGA technology.

In [12] FPGA platforms were presented by the authors. Memory operations requiring a lot of computing power are handled by this technique. Every VF domain has probes that detect idle time caused by congestion or memory access problems. [13] Have provided details on how a WSN with integrated security coprocessors for encrypted key exchange and data transfer is implemented using FPGA. It looked into digital logic systems, like fine-grained systems. Reducing FPGA power consumption has become essential for creating reliable embedded systems. [14] Have seen the architecture for specialized hardware presented. Using semiconductor regulators, the technique was implemented on the FPGA platform to minimize the latency caused by off-chip authority. In a similar vein, researchers used the look-ahead technique of adjustable voltage supply to save power in motion estimation systems.

[15] suggested a distribution method based on genetic algorithms to increase the range of randomly distributed nodes in a target area, it’s made up of a M x N grid and a group of identical WSNs (S = S1, S2, S3,..., Sn) by minimizing the quantity of sensor nodes in the unplanned distribution, To improve the area coverage, they created IDDT-GA, an improved dynamically deployment method that uses genetic algorithms. In fact, authors maximized the region covered by the sensors by minimizing the amount of sensor nodes, which also reduces the region of overlap among sensor nodes. The method described in their research employs a two-point crossover and variable length coding notation, enabling them to ensure connectivity across sensor nodes. The algorithm looks for the fewest amount of sensor nodes to cover the area, and the two-point crossover truly makes it possible for the chromosomal length to be adaptive. As a result, IDDT-GA employs an adequate quantity of nodes to cover the whole area. After then, random deployment will be employed to create zones with different intensities and high densities, while other regions with lower intensities but intriguing data may be missed due to inadequate coverage. Up order to make up for this, they include a mobility feature that increases coverage and fills in any coverage gaps. Numerous simulation data and comparisons with different methods are provided by the authors to demonstrate. [16] Genetic algorithm was used in optimizing coverage the algorithm tries to find the best node placement location, it was able to work towards maximizing the coverage area but in a state where by the element that became exposed to mutation increases, it increase the searching space size as well as increase the time taken.

[17] Developed a coverage optimization model using a hybridized weed algorithm strategy following the steps developed while improving the weed algorithm. That is, the standard deviation of normal distribution in other to balance local and global searching ability of the weed algorithm, the use of levy flight to avoid the premature convergence problem and the increase in convergence speed never the less, the algorithm has problem of time consuming.[16] Stated out in their work “Area coverage maximization under connectivity constraint in Wireless sensor networks” the problem is formulated in terms of linear programming. After that, they went over how the chromosomes are represented, selection, crossover, mutation, and lastly how the fitness function is derived using genetic algorithm that calculate the percentage of coverage and consider sensor connectivity. Through the use of numerous scenarios and modifying the amount of test cases, their concept takes into account the overlay among one or more sensors to calculate and provide the precise highest coverage, but did not consider the positioning of the nodes redundancy and cost efficiency will be at risk.

3. Genetic Algorithm

Genetic algorithms (GAs) are evolutionary optimization techniques, originally developed by[18] that simulate natural selection processes to solve complex problems across various domains, including wireless sensor networks (WSNs). Until a nearly ideal solution is discovered, genetic algorithms retain a population of viable solutions and evolve them through selection, crossover, and mutation over the course of multiple generations. As evidenced by recent developments, hybrid ways to improve GAs—such as merging GAs with local search techniques have been shown to increase convergence time and solution quality [19]. In the context of WSNs, GAs have been effectively applied to optimize node deployment strategies and energy consumption, where they can determine optimal sensor placements and operational modes (active or sleep) to extend network lifetime and coverage, as seen in the work of [20]. In addition, adaptive GAs have been created to balance exploration and exploitation; notable improvements have been reported by [21]. These adaptive GAs dynamically change parameters such as mutation rate and crossover frequency based on population diversity. Based on the work of [22] in optimizing neural network topologies, parallel GAs have made it possible to answer more complicated problems faster by utilizing contemporary parallel computing architectures. In spite of these developments, problems like managing computational costs and striking a balance between exploration and exploitation still need to be addressed. Ongoing research is concentrated on creating adaptive and hybrid strategies and fusing GAs with machine learning methods to further increase their efficacy, especially in specialized domains like WSNs.

4. Proposed System

Wireless sensor networks are widely used in numerous different functions; nonetheless, energy consumption is still a major design and management concern. Ineffective node placement tactics and inefficient sensor node operation modes are two main causes of rising power consumption, which has a detrimental effect on network performance. Furthermore, it has been shown that these problems are NP-Hard for the majority of sensor deployment formulations. Even though numerous strategies have been put out to deal with these problems, conventional ways frequently fall short of offering workable answers.

The suggested system presents a brand-new approach that uses genetic algorithm (GA) optimization to achieve energy-efficient WSN design. The primary goals of this system are to classify nodes into two operational modes active and sleep and to optimize the deployment of sensor nodes. The system is divided into two primary stages, each of which uses a different genetic algorithm to accomplish particular optimization goals. In order to augment the current static (fixed) nodes, mobile nodes are optimally placed and numbered in the first phase, which is determined using GA. The algorithm also finds the best places to divide the big monitored region into smaller subareas. The other nodes go into a low-power sleep mode during the second phase, leaving only the nodes in the active subarea to monitor. This method dramatically lowers the WSN's overall energy consumption.

4.1 Stage One: Node Deployment Strategy Using Mixed Deployment

The first stage of the proposed system focuses on the sensor node deployment strategy, utilizing a mixed deployment approach. This strategy begins with essential static (stationary) nodes and then adds mobile nodes to complete the communication network Fig (1). By combining static and mobile nodes, the system leverages the advantages of both types while mitigating their respective disadvantages. Static nodes help reduce network complexity by eliminating the need to make all nodes mobile, avoiding unnecessary movement to achieve coverage. In many cases, not all sensors need to be mobile to fulfill the coverage requirements Fig (2).

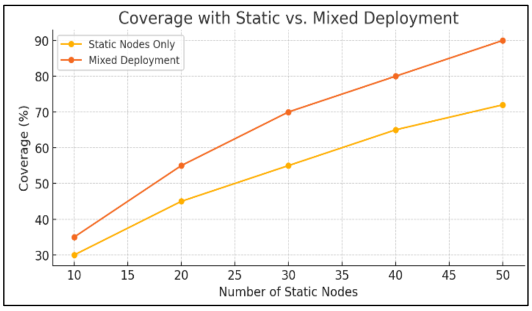

Figure 1. Coverage with static vs. mixed deployment

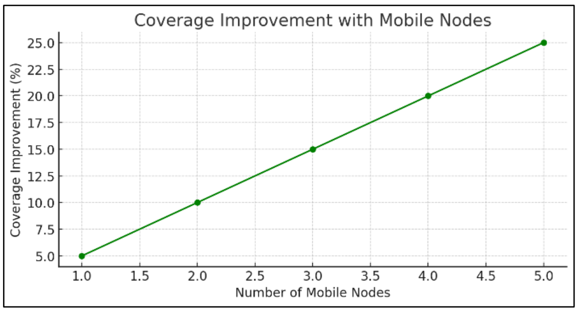

Figure 2. Coverage improvement with an increasing number of mobile nodes.

Conversely, incorporating mobile nodes helps lower the overall cost by reducing the number of static nodes needed, especially in more complex networks Fig (3).

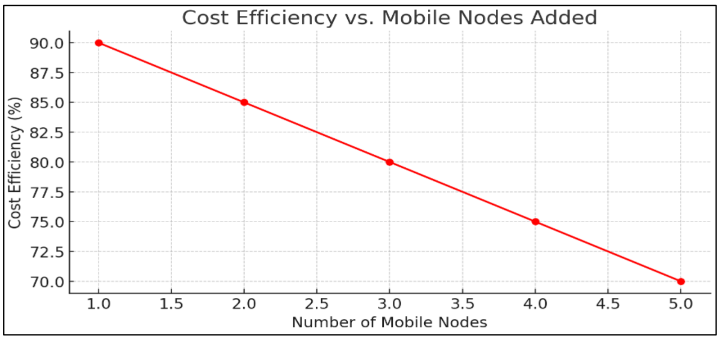

Figure 3. Cost efficiency vs. mobile nodes added

In this approach, the proposed system uses a random distribution of SNs, with the base station node remaining stationary. For instance, assume that Si static sensor nodes are randomly allocated throughout the sensing field, each having an identical sensing range represented by a circular area with radius r Fig (4). The system then gathers location data on the static sensor nodes and employs a genetic algorithm (GA) to determine the optimal number and placement of mobile nodes, proceeding with the first phase of the GA optimization as follows:

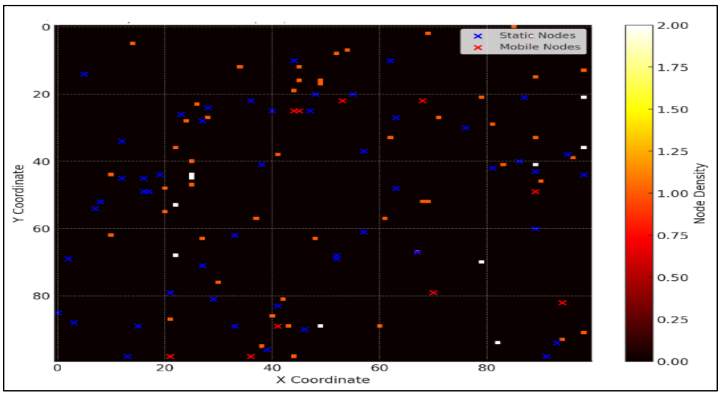

Figure 4. Deployment of static and mobile nodes

In the first suggested genetic algorithm (GA), each chromosome C_i represents the position of a mobile sensor node in the sensing area as an (X, Y) coordinate in binary form. The number of ones in a chromosome indicates the number of mobile nodes included in that solution. The population size for GA is set to 20 chromosomes. The algorithm utilizes the roulette-wheel technique is used to choose chromosomes for reproduction. A single-point crossover is employed, with a crossover rate of 0.6. Inversion mutation is performed on the offspring, with 0.02 mutation rate.

Let the chromosome Ci of length n be represented as:

$$Ci = (x_1, x_2, \dots, x_n), \qquad x_j \in \{0,1\} \dots \dots \dots (1)$$

where:

- X_j =1: A mobile sensor node is placed at the corresponding (X_j,Y_j) position.
- X_j =0: No mobile node is placed at that position.

The number of mobile nodes represented by a chromosome is the sum of ones in the binary string:

$$N_{mobile}(C_i) = \sum_{j=1}^{n} x_j \dots \dots \dots (2)$$

The fitness function evaluates the quality of each chromosome (or solution) in the population. It measures the maximum number of targets that can be detected by each mobile node, ensuring that these targets are not already covered by other mobile or static nodes. This helps to prevent redundancy and overlap in coverage areas, with each mobile node covering a distinct region. The fitness function is expressed as:

$$f(i) = f(N_{si})/\sum O_j \qquad \ldots\ldots\ldots (3)$$

As:

$$f(N_i) = \begin{cases} f(N_{si}) + 1, & D(N_{si}, O_j) \le r \quad and\ O_j \notin \{S_c, f\left(N_{\frac{s}{i}}\right)\} \\ f(N_{si}), & others \end{cases} \ldots\ldots\ldots (4)$$

This formula involves calculating the fitness function *f(i)*, which is defined as the ratio of the fitness of a node N_{si} to the sum of the observed values O_j. The condition $D(N_{si},O_j) \le r$ ensures that the distance between the sensor node and the observed target O_j is within a specific range, and the target is not covered by other sensors. This ensures optimal coverage while minimizing unnecessary duplication across sensor nodes Fig (5).

The genetic algorithm terminates either when the optimal solution is found or after completing 50 iterations. Through this process, the proposed system effectively optimizes both the number and locations of sensor nodes involved in the communication network.

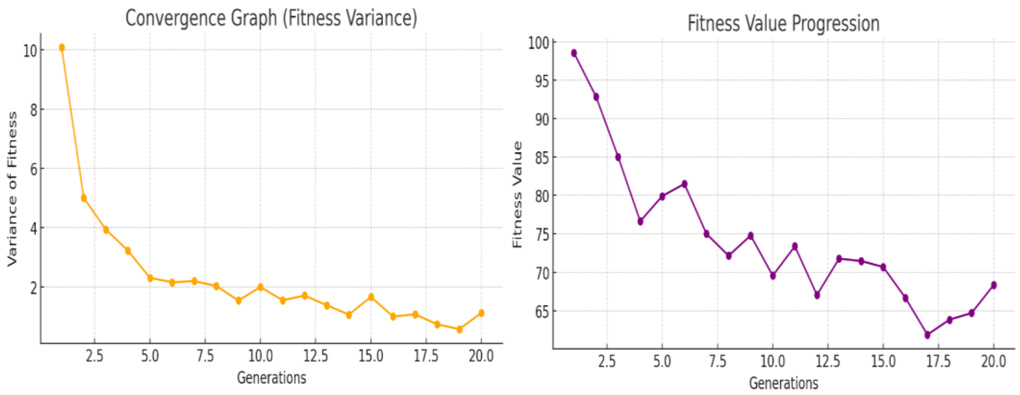

Figure 5. Fitness Variance & Progression

4.2 Stage Two: Energy-Efficient Mode Selection

The primary goal of this stage is to maximize the energy efficiency of sensor nodes by classifying them into two operational modes: active and sleep. The proposed system organizes the sensor nodes into disjoint sets, where each set is responsible for monitoring a distinct region within the area. These sets are activated in sequence; while one set is active, the remaining sets are in sleep mode, consuming significantly less energy. This approach helps minimize energy consumption and extends the overall lifespan of the network Fig (6).

To achieve optimal performance, the system aims to maximize the number of disjoint sets, which increases the number of nodes in sleep mode, thereby further reducing energy consumption. The system uses a genetic algorithm (GA) to optimize the number and distribution of sensor nodes by dividing the monitored area into smaller sub regions, Fig (7) depicting fitness value improvement over generations shows how the GA optimizes sensor node distribution over time.

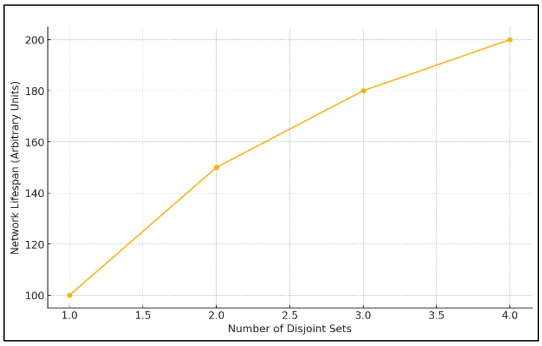

Figure 6. Network Lifespan vs. Number of Disjoint Sets

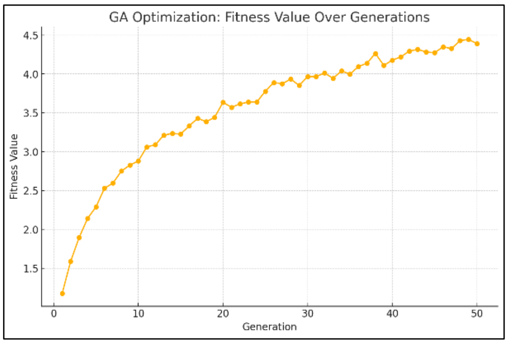

Figure 7. Fitness value over generation

The chromosomes in the second GA represent both the number and locations of the regions within the sensing field using binary encoding. The population size is fixed at 30 chromosomes to balance the exploration of the solution space and computation time. Tournament selection is used to select chromosomes for the following generation, ensuring that the fittest solutions are prioritized, the scatter plots of initial and optimized sensor node distribution Fig (8) visualize how the GA enhances coverage and efficiency.

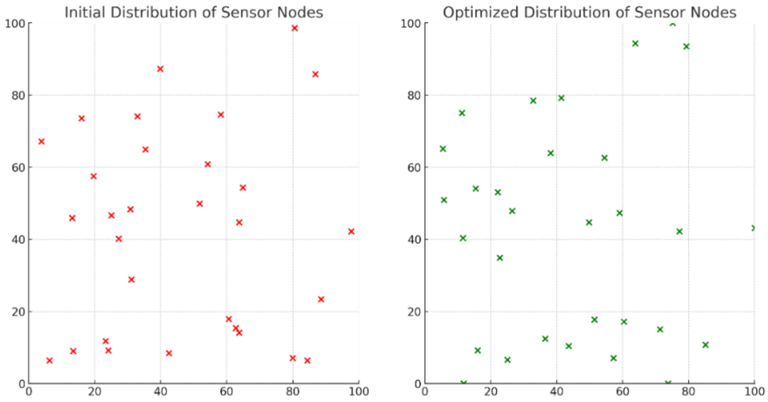

Figure 8. Optimized Distribution of Sensor Nodes

A single point crossover is performed to the chromosomes, with a crossover rate of 0.7, promoting diversity and the creation of new solutions. Inversion mutation is applied to the offspring with 0.025 mutation rate, introducing slight variations that help explore new areas of the solution space.

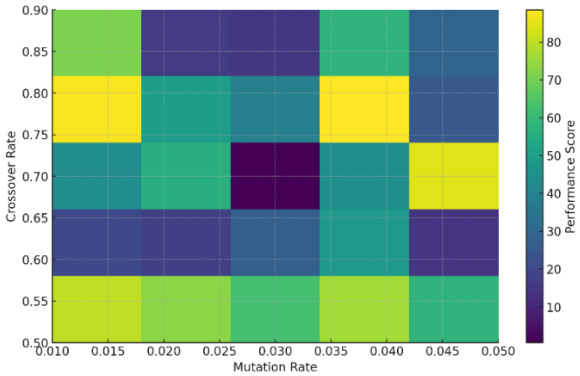

Figure 9. Impact of Crossover and Mutation Rates on GA

The fitness function for this Genetic Algorithm (GA) is formulated to evaluate the performance of region division in the sensing area for optimizing power consumption. It can be represented as:

$f(x) = \sum_{i=1}^{N}(\frac{X}{L_i} - C(x_i))$ … … … (5)

Where:

- x = Instance of regions in the sensing area
- N = Total number of regions in the sensing area
- X is the total sensing area,
- L_i is the location or importance factor for each region i,
- $C(x_i)$ is the cost of dividing the area into region i.

The 3D surface plot Fig (10) visualizes how the fitness function *f(x)* changes as the total sensing area X and the cost C(x) vary, demonstrating the efficiency of region division. This fitness function evaluates how efficiently the sensing area is divided into regions, optimizing the use of sensor nodes by minimizing redundant node activation and thereby reducing power consumption Fig (11).

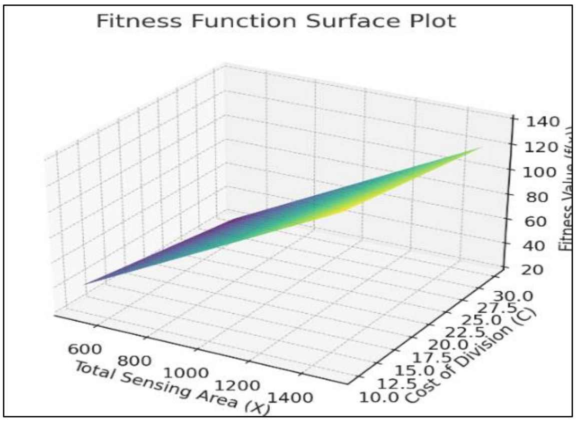

Figure 10. Fitness Function Surface Plot

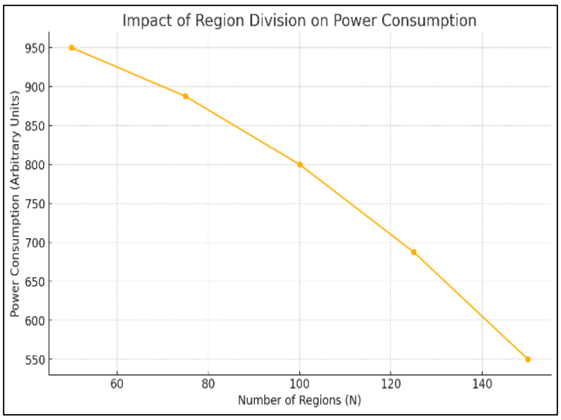

Figure 11. Impact of Region Division on Power Consumption

Genetic Algorithm terminates either upon achieving the optimal solution (i.e., minimal power consumption with optimal region division) or after completing 50 iterations. However, the system can dynamically adjust the termination condition based on different thresholds like energy savings or division cost Fig (12).

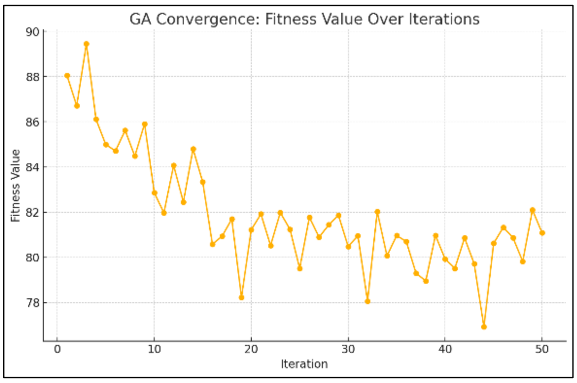

Figure 12. GA Convergence: Fitness Value Over Iterations

The convergence graph shows how the fitness value stabilizes over iterations, indicating when the GA might terminate early due to reaching an optimal solution. By using this technique, the system can optimize the WSN's power usage by dynamically turning off underutilized sensor nodes and placing them in sleep mode.

5. Conclusion

This article examined the ongoing problem of energy consumption in wireless sensor networks (WSNs), with a focus on node positioning and operational effectiveness. The suggested system presents a cutting-edge method that makes use of dual genetic algorithms (GA) to maximize sensor node deployment and operation, greatly enhancing energy efficiency. Two phases make up the system's operation. A genetic algorithm is used in the first step to position mobile sensor nodes in conjunction with static nodes in an optimal manner that ensures complete coverage while reducing the number of mobile nodes needed. By balancing the advantages of mobile and static nodes, this strategy lowers total network costs and complexity. In the second stage, the system improves energy economy by dividing sensor nodes into active and sleep modes. The system minimizes redundant energy use by carefully segmenting the monitored area into sub regions and activating just the necessary nodes for each sub region. By maximizing the number of nodes in sleep mode while preserving essential coverage, the GA optimizes this process and guarantees that the network runs as efficiently as possible.

Through simulations of a WSN intended for radiation site detection, the suggested system was verified and shown to consume significantly less energy than conventional techniques. The outcomes demonstrated both a noteworthy extension of the network's operating lifetime and an improvement in accuracy. These results imply that the suggested method is very successful for WSN real-time applications, providing a strong answer to the problem of energy efficiency in sensor networks.

References

1. García-Nájera, A., S. Zapotecas-Martínez, and K. Miranda, Analysis of the multi-objective cluster head selection problem in WSNs. Applied Soft Computing, 2021. 112: p. 107853.
2. Ouni, R. and K. Saleem, Framework for sustainable wireless sensor network based environmental monitoring. Sustainability, 2022. 14(14): p. 8356.
3. Nourildean, S.W., M.D. Hassib, and Y. Mohammed, Internet of things based wireless sensor network: a review. Indones. J. Electr. Eng. Comput. Sci, 2022. 27(1): p. 246-261.
4. Lee, J.-W., B.-S. Choi, and J.-J. Lee, Energy-efficient coverage of wireless sensor networks using ant colony optimization with three types of pheromones. IEEE Transactions on Industrial Informatics, 2011. 7(3): p. 419-427.
5. Srivastava, A. and P.K. Mishra, A survey on WSN issues with its heuristics and meta-heuristics solutions. Wireless Personal Communications, 2021. 121(1): p. 745-814.
6. Jondhale, S.R., et al., Fundamentals of wireless sensor networks. Received Signal Strength Based Target Localization and Tracking Using Wireless Sensor Networks, 2022: p. 1-19.
7. Singh, O., et al., Multi-objective optimization in WSN: Opportunities and challenges. Wireless Personal Communications, 2021. 121(1): p. 127-152.
8. Sasi, S.B. and R. Santhosh, Multiobjective routing protocol for wireless sensor network optimization using ant colony conveyance algorithm. International Journal of Communication Systems, 2021. 34(6): p. e4270.
9. Maheshwari, P., A.K. Sharma, and K. Verma, Energy efficient cluster based routing protocol for WSN using butterfly optimization algorithm and ant colony optimization. Ad Hoc Networks, 2021. 110: p. 102317.
10. Shafiq, M., et al., Systematic literature review on energy efficient routing schemes in WSN–a survey. Mobile Networks and Applications, 2020. 25: p. 882-895.
11. Patil, V. and S. Deshpande, Design of fpga soft core based wsn node using customization paradigm. Wireless Personal Communications, 2022. 122(1): p. 783-805.
12. Misra, Y., K. Krishnaveni, and A.S. Rajasekaran, Implementation of NLOS based FPGA for distance estimation of elderly using indoor wireless sensor networks. Materials Today: Proceedings, 2022. 57: p. 2299-2306.
13. Toubal, A., et al., FPGA implementation of a wireless sensor node with built-in security coprocessors for secured key exchange and data transfer. Measurement, 2020. 153: p. 107429.
14. Ompal, V.M. Mishra, and A. Kumar, Zigbee internode communication and FPGA synthesis using mesh, star and cluster tree topological chip. Wireless Personal Communications, 2021. 119(2): p. 1321-1339.
15. Wang, L., Y. Luo, and H. Yan, Optimization analysis of node energy consumption in wireless sensor networks based on improved ant colony algorithm. Sustainable Energy Technologies and Assessments, 2024. 64: p. 103680.
16. Tossa, F., et al., Area coverage maximization under connectivity constraint in wireless sensor networks. Sensors, 2022. 22(5): p. 1712.
17. Zhu, F. and W. Wang, A coverage optimization method for WSNs based on the improved weed algorithm. Sensors, 2021. 21(17): p. 5869.
18. Holland, J., adaptation in natural and artificial systems, university of michigan press, ann arbor,". Cité page, 1975. 100: p. 33.
19. Yang, X., Zhang, Y., & Li, M. (2022). A Hybrid Genetic Algorithm with Simulated Annealing for Efficient Scheduling. Applied Soft Computing, 115, 107554.
20. Zhang, H., Zhou, X., & Wang, J. (2024). Optimization of Sensor Node Deployment in Wireless Sensor Networks Using a Genetic Algorithm. Wireless Networks, 30(1), 67-81
21. Jiang, Y., et al., A novel binary-addition simplified swarm optimization for generalized reliability redundancy allocation problem. Journal of Computational Design and Engineering, 2023. 10(2): p. 758-772.
22. Smith, T., Wang, L., & Chen, Y. (2023). Parallel Genetic Algorithms for Optimizing Neural Network Architectures. IEEE Transactions on Neural Networks and Learning Systems, 34(5), 1120-1133.