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Pruning and Validation Techniques Enhanced Genetic Algorithm for Energy Efficiency in Wireless Sensor Networks

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ABSTRACT

Designing energy-efficient systems in Wireless Sensor Networks (WSNs) is challenging as each sensor has limited energy. This research paper suggests a combined method that merges a Genetic Algorithm (GA) with pruning and validation strategies to enhance sensor network routing paths to minimize energy usage. The GA uses variable-length chromosomes to depict paths from a source sensor node to a sink node. Initial populations are created randomly and genetic mechanisms such as selection, crossover, and mutation are applied to refine these paths for efficiency. Pruning methods are then used to remove redundant nodes in the obtained paths ensuring energy-efficient routing. Path validation in the GA processes ensures that each path adheres to the transmission range limits of sensors. The experiments use setups with 20, 50, 100, and 150 sensor nodes. Results have shown that this approach chooses the best paths with minimal energy consumption and it is superior to the Ant Colony Optimization (ACO) algorithm.

1. INTRODUCTION

Sensors can monitor environmental and physical phenomena, like humidity, temperature, vibration, motion, and sound. So Wireless sensor networks are broadly used in various fields such as monitoring surrounding events in greenhouses (such as humidity and temperature), disaster alarm applications, smart buildings, traffic control, smart homes, battlefield surveillance, and health surveillance. The objective of a WSN is usually based on the application [1-5].

The physical traits acquired by the sensors from the surroundings are translated into detectable electrical impulses. Pressure, mass, temperature, or warm bodies such as people are mentioned as these traits. The microprocessor processes the electrical impulses to provide outputs that agree to a set of measures. The output is sent to the base station or sink node [6, 7].

The Internet of Things (IoT) links numerous types of wireless and wired networks to the Internet, consequently connecting objects and making a vast network for monitoring, control, and analysis [8, 9]. IoT has contributed to various life fields such as smart cities, smart farming, smart supply chains, "smart home" devices, and health [10, 11].

WSNs have drawn the attention of numerous researchers in recent years as a result of their widespread application. In WSNs, sensors perceive, send out, and cooperatively collect information. A definite amount of energy will be spent during these processes. However, the sensors are operated using batteries with limited power which will affect the data transmission in WSN. The entire network will be suspended once the battery expires and there is no time to change the power supply. Consequently, the energy efficiency in the WSNs with limited energy to expand the lifespan of the whole network has turned into a constraint in WSN's practical applications [12, 13].

However, effectively utilizing energy to increase the network's operational lifetime presents a significant issue in deploying WSNs. Many optimization strategies, including Genetic Algorithms, Ant Colony Optimization, Artificial Bee Colony (ABC), Multi-Objective Genetic Algorithms (MOGA), and others have been studied in the current literature in Section II, some of the studies combine more than one optimization method. Nevertheless, issues with computational complexity, scalability, path validity, and overall energy efficiency still need to be resolved.

Despite these efforts, there is still a need for a better methodology to overcome the limitations of current ways in terms of reducing computational overhead, improving solution feasibility as well as increasing energy efficiency throughout the network.

In This work, an enhanced variable chromosome length genetic algorithm with pruning and validation techniques is proposed for energy efficiency in WSNs.

- Validation techniques are used to ensure the feasibility of the generated paths considering the sensor transmission range constraints to enhance the reliability of the routing paths.
- Pruning techniques are used to eliminate redundant nodes to reduce overall energy consumption.

The outcomes are compared with the outcomes of the ACO algorithm. The proposed methodology is applied within WSNs consisting of 20, 50, 100, and 150 nodes respectively. The experimental results prove that the proposed method shows performance better than the ACO in terms of energy consumption and time complexity.

This paper is arranged into the following sections: Section II presents recent related works in wireless sensor networks' energy consumption. Section III presents the proposed methods for optimizing energy consumption in WSNs using enhanced VLGA. Section IV presents the experimental settings and results. Finally, Section V concludes the paper and suggests future works.

2. RELATED WORKS

Shanthi [14] suggests an improvement in the Genetic algorithm was proposed that entitled a Dominant GA to find the optimal routing path that uses less energy and to determine the optimal trajectory for mobile sensor nodes. The proposed method applied a mutation operator and the connection-oriented crossover to preserve the solutions' feasibility. Two different simulation scenarios were applied. The first one explored the energy efficient routes to transport the data from the source node to the sink node, and the second one obtained the energy efficient-route among all local data nodes for mobile sensor nodes.

Bhola et al. [15] propose the LEACH routing protocol along with the GA to improve energy efficiency and the lifespan of WSNs. LEACH is a hierarchical protocol that determines cluster heads (CH) of the WSN, CH collects the data and compresses it before sending it to the sink node. The optimal route is found by GA using its fitness function. MATLAB simulator results show an energy consumption rate of up to 17.39% between the proposed and recent existing works.

Al Mazaideh and Levendovszky [16] suggest a Compressive Sensing-based method for data transmission efficiently in WSNs utilizing Multi-Objective GA to improve the sensing matrix, the number of measurements, and transmission range. The methodology balances accuracy and energy efficiency. It creates a multi-hop path according to the optimized values. Experiments and simulations demonstrate how the user benefits from the Pareto front of MOGA to select the best combination of the transmission range and the number of measurements to balance accuracy and energy efficiency.

Alshattnawi et al. [17] present a hybrid approach that incorporates two algorithms based on population: An Artificial Bee Colony and a genetic algorithm with two clustering methods. This proposed study aims to extend the WSN's lifespan by reducing the amount of power used by each sensor node. The GA was initialized by the initial population that was enhanced by ABC. Furthermore, two methods of clustering were presented; clustering based on a genetic algorithm and K-means clustering alongside the implementation of the LEACH protocol. The simulation outcomes show efficiency in a WSN’s lifetime expansion.

Heidari et al. [18] present a clustering and routing method based on genetic algorithms and equilibrium. The sensor nodes are grouped in clusters and the best cluster heads are selected in the first stage using GA. In the next stage, where the cluster head receives the data that each node has collected and sends it in the optimal route using an equilibrium optimization algorithm to reduce energy consumption in WSN. The approach was simulated and tested using MATLAB software and showed outperforming outcomes.

Table 1. The summary of related work

No.	Research	Year	Methodology	Pros	Cons
1	Shanthi [14]	2020	Dominant GA	• Reduce energy consumption • Preserves solution feasibility • Effective for mobile sensor nodes	• DGA involves more complex operations compared to simpler routing protocols. This complexity might make challenges in real-world implementations.
2	Bhola et al. [15]	2020	GA-based LEACH	• Improved energy efficiency, network lifetime, and data delivery rates.	• The integration of a GA with LEACH may adds computational complexity. • The fixed clustering used by the LEACH algorithm may not be ideal with dynamic network conditions.
3	Al Mazaideh and Levendovszky [16]	2021	MOGA	• Efficient data transmission • Balances accuracy and energy efficiency • Optimized sensing matrix and transmission range	• Potentially high computational overhead for MOGA optimization.
4	Alshattnawi et al. [17]	2022	Hybrid ABC and GA, K-mean and LEACH clustering	• Extends WSN lifespan • Efficient clustering using GA and K-means • ABC enhances initial population	• Complexity in hybrid approach implementation • High computational resources needed for ABC and GA.
5	Heidari et al. [18]	2022	GA and Equilibrium optimizer	• Reduces energy consumption • Efficient cluster head selection • Optimal routing using equilibrium optimization	• Complexity in implementing multiple optimization techniques.
6	Alkanhel et al [19]	2023	A multi-swarm optimization-based GA to choose an efficient Cluster Head	• Enhances WSN lifespan • Optimizes routing paths • Effective cluster head selection	• Complexity in multi-swarm optimization • High computational and energy resources required.
7	Gunigari and Chitra [20]	2023	ACO, E-RARP routing protocol, and GEC algorithm	• High-quality communication channels to save energy • Increases network lifetime	• Complexity in implementing game theory and ACO combined
8	Hamza et al. [21]	2023	GF, PSO, and Tabu Search Techniques	• Enhances WSN lifetime • Reduces energy consumption • Improves end-to-end delay and packet loss rates	• High complexity in combining multiple optimization techniques. • May require significant computational resources.

Alkanhel et al. [19] provide a technique to improve the network's lifespan and routing optimization that uses Multi-Swarm optimization (MSO) based on a Genetic Algorithm and adaptive hierarchical clustering-based routing protocol. This technique focuses on clustering-based power consumption routing to ensure constant coverage of the entire area and maintain node energy consumption balance through distributed data transmission modification. The MSO-GA algorithms are used to select the optimal Cluster Head. The results of the study show that the suggested MSO-GA with Hill Climbing is efficient because it decreases average packet loss and end-to-end delay while increasing the number of clusters formed and the average energy used.

Gunigari and Chitra [20] suggest a hybrid energy-efficient and reliable ACO based on the E-RARP Routing protocol and game theory-based energy-efficient clustering algorithm (GEC). To increase energy efficiency, the E-RARP protocol offers dependable communications and high-quality channels of communication. Using the GEC, every sensor node is viewed as a member of the team. Based on the amount of idle playback time during the active phase, the sensor node can select strategies that will benefit it and then determine whether or not to rest. In addition to enhancing network lifetime and data transmission, the suggested E-RARP-GEC uses the least amount of energy as compared to the current methods.

Hamza et al. [21] use a novel Grey Wolf Improved Particle Swarm Optimization with Tabu Search Techniques (GW-IPSO-TS) method. The proposed GW-IPSO-TS enhances the selection of CHs and the routing path of each CH, increases the lifetime and energy efficiency of the WSN, improves the packet loss rate and end-to-end delay, enhances the estimation of dead nodes, alive nodes, convergence rate, standard deviation, and network survival index of sensor nodes.

Table 1 shows the summary of the related works. Energy efficiency in wireless sensor networks has been subject to research by leading scholars who have used a combination of optimization techniques. However, these methods are characterized by poor scalability and huge time complexities associated with the same.

To overcome these shortcomings, this study proposes a strategy to improve the energy efficiency of WSNs using a Genetic Algorithm combined with pruning and validation techniques. The goal is to alleviate the issues that arise from combining multiple optimization algorithms into one system.

3. THE PROPOSED METHOD

An energy-efficient WSNs-based enhanced GA by the pruning and validation techniques is proposed in this work. Four topologies are proposed consisting (of 20, 50, 100, and 150) randomly distributed along with one base station (BS) or sink node. The dimensions in meters and number of sensors are shown in Table 2.

Table 2. WSNs' four topologies

No. Sensors	WSN Dim.
20	200*200 m^2
50	500*500 m^2
100	500*500 m^2
150	500*500 m^2

In this paper Variable Length Genetic Algorithm (VLGA) is proposed for energy efficiency in WSNs to select an optimal route from each sensor to the base station or sink node in terms of energy cost to improve the WSN lifespan. The using of variable chromosome length is suitable for selecting diverse multi-hop paths considering minimum energy cost. The pruning step is used to eliminate unnecessary nodes in the obtained path that do not add to the path efficiency to ensure that the routing path is optimal and uses less energy. During GA operations path validation is essential to ensure that the obtained path meets the constraints of the range of transmission of the sensor nodes confirming the feasibility and reliability of the obtained paths. The validation step is called in the initialized random population step to generate feasible search space, and in crossover and mutation steps to confirm path validation after the changes done by these steps.

3.1 Genetic algorithm overview

GA is a meta-heuristic, stochastic optimization algorithm inspired by natural selection and genetics and created by John Holland in 1975 [22]. The main operators of GA are selection, mutation, and crossover. The solution of GA is encoded in a sequence known as a chromosome. A chromosome consists of a set of elements denoted as genes. In the original implementation of the GA, every chromosome needs to have the same number of genes. To evaluate the fitness value of each chromosome an objective function is used. The GA starts with a population which is a set of chromosomes [23].

The basic procedure of GA includes three operators [24]:

(1) Selection: In this operation, the fitter chromosomes are selected in the population for reproduction.

(2) Crossover: In this operation, the offspring are created by exchanging the genetic materials of two Chromosomes. This operator roughly mimics biological recombination

(3) Mutation: This operator arbitrarily changes some genes in a chromosome.

GA works through several steps [24]:

(1) Initial population: GA begins with a population of N chromosomes that are randomly produced and represent potential solutions to the issue.

(2) Evaluation: for every chromosome (x) in the population, the fitness function f(x) is calculated.

(3) Repeat steps from (4)-(6) till N offspring are produced:

(4) Selection: GA selects a pair of parent chromosomes from the present population, one type of selection is based on the highest fitness function, and there are several selection methods.

(5) Crossover: GA considers the crossover likelihood to crossover the parent pair at an arbitrarily selected point, also there are several crossover methods.

(6) Mutation: GA mutates the two offspring considering the mutation likelihood and puts the new offspring in the new generation.

(7) Substitute the current population with the new one.

(8) Go to step 2.

(9) Termination: either by reaching maximum iteration or by finding the optimal path.

A type of GA where the length of chromosomes is variable is referred to as a variable length genetic algorithm (VLGA). VLGA is applied in many fields, such as network intrusion detection systems [25], and in energy-efficiency in WSNs [26].

3.2 The proposed VLGA

In this work, the length of the optimal route between each source node to the sink node can vary so VLGA with variable chromosome length is proposed to find optimal paths.

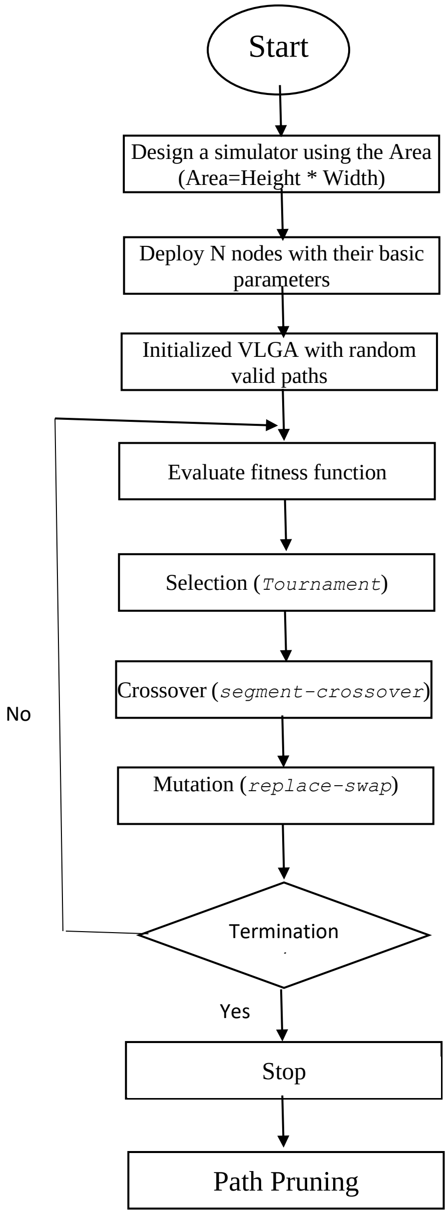


Figure 1. The flowchart of the proposed VLGA system

The proposed enhanced VLGA model consists of several steps to find the optimal route from the specific source node to the destination node. The VLGA steps are illustrated in the proposed system flowchart in Figure 1. After setting up the sensor nodes in the WSN an initial population of random paths from the sensor node to the destination node (i.e. sink node) is generated, and apply path validation to ensure that the paths are all valid, as shown in Algorithm 1.

After that, the randomly generated paths in the initial population are evaluated using the fitness function which is the energy cost of the path, the proposed model is considered a minimization optimization problem.

After evaluating the initial population, parents are selected using the tournament selection method with minimum energy cost. The parents enter the crossover step (segment-based crossover) to reproduce offspring. The crossover function iterates across the segments of parent1 and later parent2, trying to combine parents' segments into the offspring path. This method intends to fuse the characteristics of both parents, obtaining new path arrangements. The new offspring (i.e. paths) are validated in terms of the transmission range, as shown in Algorithm 2.

Algorithm (1): Initialize_Population

Input:
Sensor nodes positions
population_size
max_path_length
Distance_Range // transmision constraint
Output:
population

```
population = []
FOR i = 0 to population_size - 1 DO:
    valid_path_found = False
    WHILE NOT valid_path_found DO:
        path = [source_node]
        FOR j= 0 to max_path_length - 2 DO:
            next_nodes= node WHERE: (node IS NOT in path AND distance(last node in path, node) <= Distance_Range)
            IF next_nodes Is-empty THEN: BREAK
            next_node = random choice from next_nodes
            ADD next_node TO path
            IF next_node IS base_station OR distance(next_node, base_station) <= Distance_Range THEN:
                ADD base_station TO path
                valid_path_found = True
                BREAK
    ADD path TO population
RETURN population
```

Algorithm (2): Crossover

Input:
parent1
parent2
Output:
child

```
child = [ source_node]
parent1_segments = parent1[1:-1]
parent2_segments = parent1[1:-1] // exclude source and sink nodes
FOR each node IN (parent1_segments + parent2_segments) DO:
    IF node IS NOT in child AND distance (last node in child, segment) <= Distance_Range THEN:
        ADD segment TO child
    IF distance (last node in child, base_station) <= Distance_Range THEN:
        ADD base_station TO child
ELSE: RETURN parent1
RETURN child IF is_path_valid(child) IS True
```

For mutation, two mutation techniques a swap and replace mutation are considered to mutate the offspring based on the mutation rate. In swap mutation, two nodes (except the source and the sink nodes) are selected randomly and swapped. This helps in reordering visits to middle nodes, which can lead to finding a more efficient routing path, as illustrated in Algorithm 3. The validation step is crucial in both crossover and mutation steps to ensure that the new paths are valid. GA iterates until it finds the optimal route and terminates.

Algorithm (3): Mutation
Input: path num_nodes **Output:** mutated_path
mutated_path = path FOR 10 iterations DO: mutation_type = random choice between 'swap' and 'replace' IF mutation_type IS 'swap' THEN: i, j = two unique random indices between 1 and length of mutated_path – 2 // *exclude source and sink node* SWAP elements at indices i and j in mutated_path ELSE IF mutation_type IS 'replace' THEN: i = random index between 1 and length of mutated_path - 2 replacement = random node between 0 and num_nodes - 1 IF replacement IS NOT in mutated_path AND distance(node at index i - 1 in mutated_path, replacement) <= Distance_Range AND distance(replacement, node at index i + 1 in mutated_path) <= Distance_Range THEN: element at index i in mutated_path = replacement IF is_path_valid(mutated_path) IS True THEN: RETURN mutated_path

3.3 Prune path and validation techniques

Algorithm (4): Pruning the path
Input: path **Output:** pruned-path
improved = True WHILE improved = True DO: improved = False FOR i = 1 TO length of path - 2 DO: pruned_path = path WITHOUT element at index i IF is_path_valid(pruned_path) IS True AND fitness(pruned_path) <= fitness(path) THEN: path = pruned_path improved = True BREAK RETURN path

Algorithm (5): Validation Technique
Input: path **Output:** true or false
FOR i = 0 TO length of path - 2 DO: IF distance(node at index i in path, node at index i + 1 in path) > Distance_Range THEN: RETURN False RETURN True

The prune path function is a post-GA optimization step that is run after the initial operations of the Genetic Algorithm to enhance the paths that have been already found by eliminating unnecessary nodes as explained in Algorithm 4. This procedure evaluates the nodes on the path (except the source and sink nodes) at each iteratively either based on the criterion of energy efficiency or equal efficiency, and after eliminating the ones that do not satisfy the criticality of WSNs the output path remains valid.

To check the path validity is_path_valid method is used, the implementation of it is explained in Algorithm 5.

3.4 The objective function

The objective function of this model is the minimum energy cost of selected paths to improve the energy consumption of the sensor nodes and save the energy of the whole WSN to expand its lifetime. The objective function is computed by considering the energy consumption for each sensor node and computing the overall energy consumption. The energy consumed by a single node during transmission can be calculated using Eq. (1) and Eq. (2) [27].

$$\mathrm{E_{tx}} = (\mathrm{E_{elec}} + \mathrm{E_{amp}} \times \mathrm{d}^2) \times \mathrm{L} \tag{1}$$

where, E_{elec} is the amount of energy consumed by the transmitter or receiver circuitry (in Joules/bit). $Eamp$ is the amount of energy consumed to transmit a bit over the air (in Joules/bit/m^2), d is the distance between nodes, and L is the number of transmitted bits. The reception energy consumed by a node during reception can be calculated using Eq. (2).

$$\mathrm{E_{rx}} = \mathrm{E_{elec}} \times \mathrm{L} \tag{2}$$

The value of $Eelec$ is often between 50 to 150 nJ/bit. A common value used in many studies is 50 nJ/bit=50×10 −9 J/bit. While the value of $Eamp$ is 100 pJ/bit/m2 = 100×10−12 J/bit/m^2.

3.5 The distance measures

The distance measure considered in this work to compute the distance between nodes is the Euclidean distance measure that is given in Eq. (3) [28]:

$$D = \sqrt{(x_2 - x_1) + (y_2 - y_1)} \tag{3}$$

4. EXPERIMENTAL RESULTS

This section illustrates the experimental results of the four topologies using enhanced VLGA and ACO algorithms. The suggested method is implemented in Python for effective implementation and evaluation. The results are evaluated in terms of energy consumption and execution time. The proposed method is implemented with the following laptop specifications:

- Processor: 11th Gen Intel(R) Core (TM) i7-11800H @ 2.30GHz 2.30 GHz
- RAM: 16.0 GB (15.7 GB usable)
- Microsoft Windows 11 Pro. 64-bit operating system, x64-based processor

Random sensor locations are used with four topologies (20, 50, 100, and 150) to test the proposed methods. The selection of the four topologies is based on how the related works set their simulation, they start with a small number of nodes and enlarge the network to increase the challenge and check the method performance. The enhanced VLGA shows performance better than ACO in terms of energy cost and time complexity. The parameters of the genetic algorithm are as follows: population size = 30, max path length = 10, max generations = 20, tournament size = 5, and mutation rate = 0.1. while the ACO's parameters are: number of ants = 20, max iterations = 100, and cycles = 100.

The optimal route from sensor 7 to the sink node in 20 node-topology selected by VLGA and ACO are shown in Figures 2 and 3, respectively. VLGA achieved 0.00119 joules energy cost and ran within 0.003 seconds by selecting the path (Sensor 7, Sensor 0, and Sink node). ACO achieved 0.00125 joules energy cost and ran within 0.06 seconds by selecting the path (Sensor 7, Sensor 9, Sensor 2, and Sink node).

The optimal path from sensor 29 to the sink node in the 50 sensor - topology determined by VLGA and ACO are shown in Figures 4 and 5. VLGA achieved 0.0055 joules energy cost and ran within 0.02 seconds. ACO achieved 0.0064 joules of energy cost and ran within 0.18 seconds.

Figures 6 and 7 display the optimal paths from sensor 52 to the sink node in the 100-node topology selected by the proposed method and the ACO, respectively. Figures 8 and 9 display the optimal paths from sensor 107 to the sink node in the 150-sensor topology determined by the proposed method and the ACO, respectively.

Table 3 shows the summary of the conducted results of the proposed method and the ACO algorithms in terms of average energy cost and time complexity.

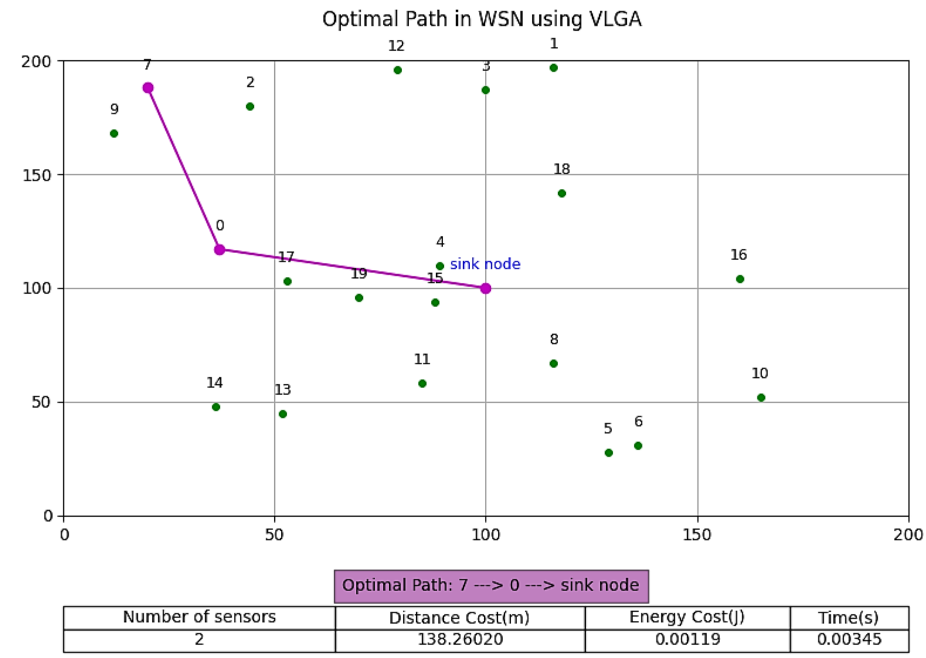


Figure 2. The optimal route from sensor 7 to the sink node in 20 node -topology using enhanced VLGA

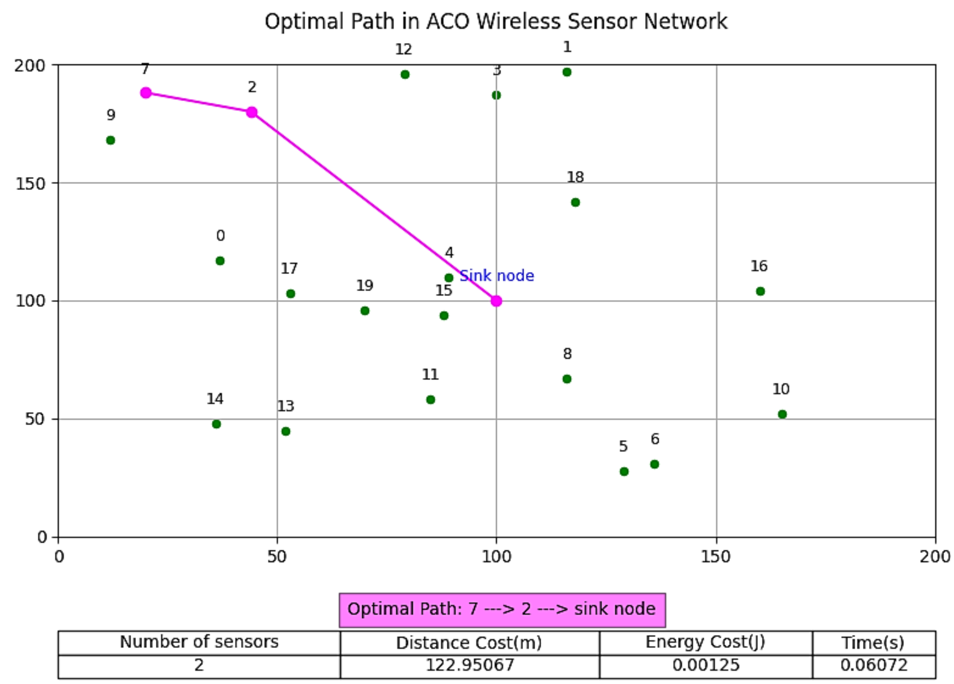


Figure 3. Selected route from sensor 7 to the sink using the ACO algorithm in 20 node-topology

The proposed method achieved outcomes better than traditional ACO by adhering to transmission range constraints in validation techniques and pruning the optimal path to ensure the paths considered are valid. This prevents wasted computational effort on invalid paths, enhancing the overall efficiency of the algorithm. The Proposed method achieved outcomes better than traditional ACO by adhering to transmission range constraints in validation techniques to ensure the paths considered are valid and prevent wasted computational effort on invalid paths to increase the algorithm's overall performance. The pruning technique is intended to eliminate redundant nodes to reduce overall energy consumption.

Table 3. The comparison between the proposed enhanced VLGA method and ACO algorithms

Algorithm	Topology 20		50	
	Avg. Time	Avg. energy	Avg. Time	Avg. energy
ACO	0.05224	0.0007	0.1801	0.0027
Proposed VLGA	0.00287	0.0006	0.0125	0.0025
Algorithm	**100**		**150**	
	Avg. Time	Avg. energy	Avg. Time	Avg. energy
ACO	0.4514	0.0026	0.83753	0.0030
Proposed VLGA	0.0662	0.0019	0.1083	0.0019

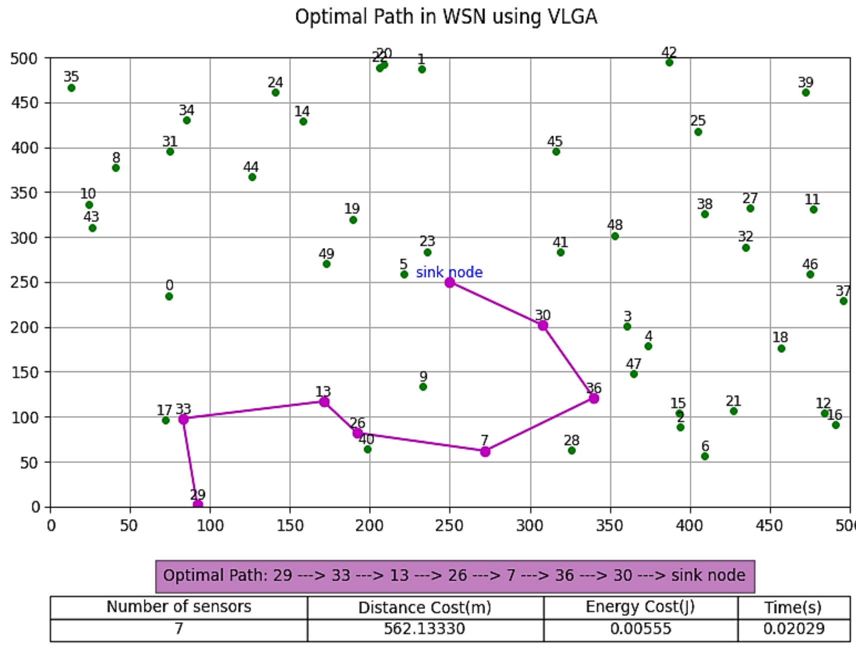


Figure 4. Depiction of the enhanced VLGA selected route for the source sensor 29 in 50 sensor-topology

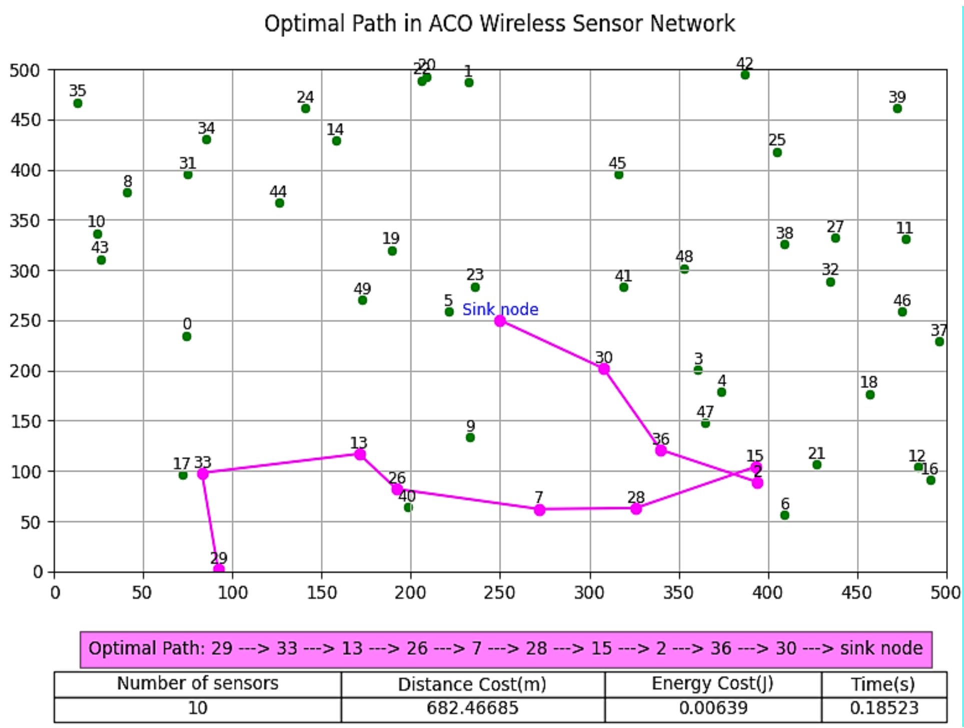
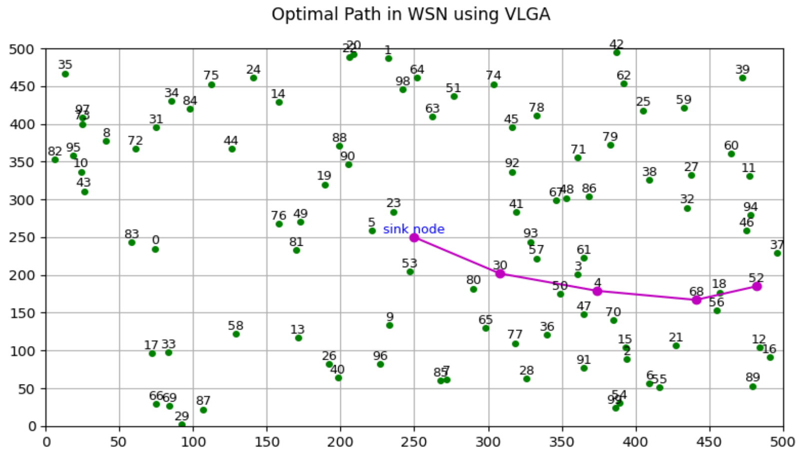
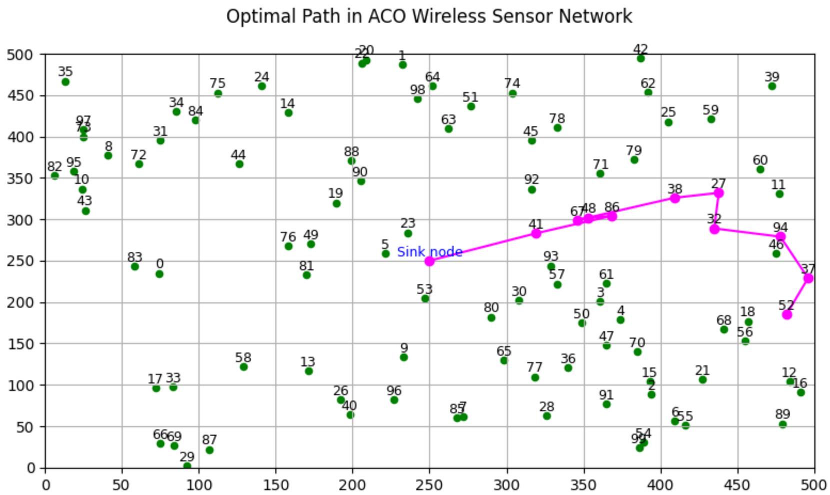


Figure 5. Depiction of the ACO selected route for the source sensor 29 in 50 sensor-topology



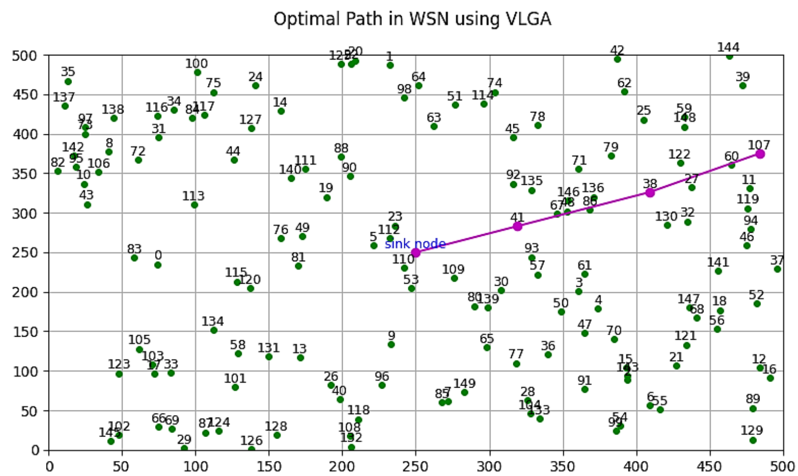
Number of sensors	Distance Cost(m)	Energy Cost(J)	Time(s)
4	258.02227	0.00217	0.09217

Figure 6. The source sensor 52 route in a 100-node topology selected by the enhanced VLGA



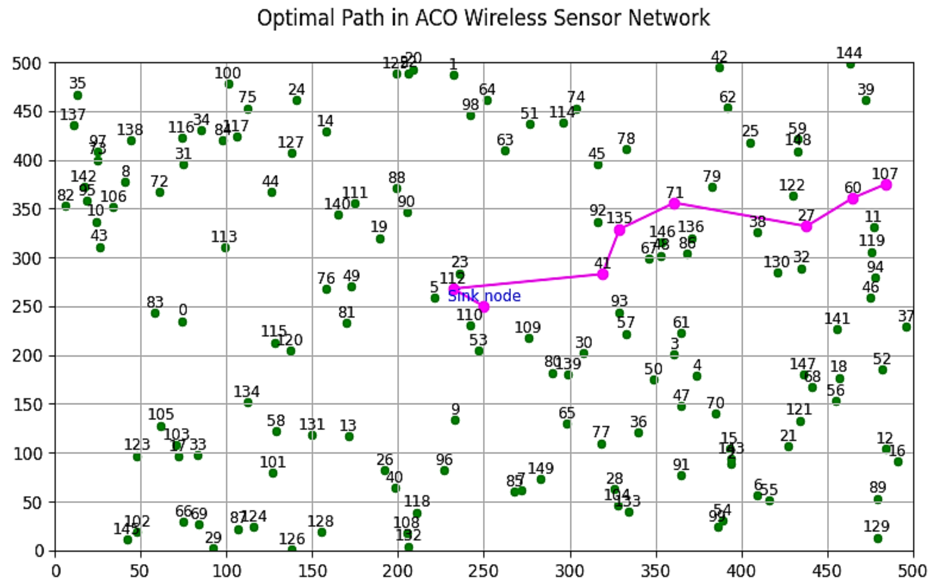
Number of sensors	Distance Cost(m)	Energy Cost(J)	Time(s)
10	437.26728	0.00341	0.36956

Figure 7. The source sensor 52 route in a 100-node topology selected by the ACO



Number of sensors	Distance Cost(m)	Energy Cost(J)	Time(s)
3	265.81791	0.00275	0.10997

Figure 8. Optimal sensor-to-sink route from sensor 107 in a 150-sensor topology using the VLGA algorithm



Optimal Path: 107 ---> 60 ---> 27 ---> 71 ---> 135 ---> 41 ---> 112 ---> sink node

Number of sensors	Distance Cost(m)	Energy Cost(J)	Time(s)
7	346.56038	0.00287	0.67075

Figure 9. Optimal sensor-to-sink route from sensor 107 in a 150-sensor topology using the ACO algorithm

5. CONCLUSION AND FUTURE WORKS

In this work, pruning and validation techniques improved the performance of the variable chromosome length genetic algorithm to exploit its evolutionary capability for route optimization toward energy conservation in WSNs. From the findings of this study, it is shown that the proposed method is stable and effective. With the VLGA achieving optimal solutions and outperforming ACO; it has become even more attractive for real-time WSN applications. Path pruning and validation approaches are two important factors that enable VLGA to perform effectively.

The validation technique aims at ensuring only valid paths are considered, thus reducing computational complexity as well as facilitating convergence. The pruning technique is designed to remove unnecessary nodes hence decreasing the average time required to find optimum paths as well as reducing energy usage in general. Adaptive mutation and crossover operations also participate significantly in maintaining population diversity to avoid premature convergence. Based on the attributes of the WSN, the proposed VLGA tunes its operations dynamically intending to find an efficient exploration of solution space while achieving better optimization results.

As part of future work, clustering with the proposed method can be considered for a reduction in time complexities plus improvement in route selection for large-scale networks.

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