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Energy-Optimized DV-HOP Localization in Wireless Sensor Networks VIA Genetic Algorithm

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Abstract: Wireless sensor networks (WSNs) are based on the need to localize in order to enable their application in environmental monitoring, target tracking and disaster management. Although the DV-Hop algorithm is one of the most popular range-free localization algorithms due to its low cost and simplicity, it suffers from severe localization errors and energy consumption in large scale and irregular network topologies. In this paper, an energy-efficient DV-Hop localization algorithm, which uses a Genetic Algorithm (GA), is proposed to achieve a higher positioning accuracy and minimized the total energy consumption in WSNs. To estimate the solution of the main DV-Hop parameters including the average error of the hop distance and the choice of anchor weight, the suggested algorithm is based on GA, constructing a multi-objective fitness function that minimizes the localization error and the communication energy expenditure simultaneously. In variable network environments, the algorithm is able to find near optimal solutions by evolutionary mechanisms, such as selection, crossover and mutation. It is demonstrated that the proposed framework based on GA-assisted DV-Hop localization shows good localization performance and lower energy consumption in communication comparing with conventional DV-Hop and clustering localization. Compared with the Existing GA method, the proposed framework reduces the average localization error by approximately 48–52%, while the maximum localization error is reduced by 40%. The proposed scheme also demonstrates improved performance across different anchor densities and threshold conditions. The proposed scheme is applicable to energy constrained and large scale WSN application as it does not require any additional hardware and preserves the range free feature of DV-Hop. To conclude, genetic algorithm and DV-Hop localization can be used to localize nodes in WSN to achieve high accuracy with less energy consumption and with high scalability.

Keywords: DV-Hop Localization, Energy Optimization, Genetic Algorithm (GA), Localization Accuracy, Range-Free Localization, Wireless Sensor Networks (WSNs).

1. Introduction

WSNs are extremely dense networks of low-power sensor nodes that are sparsely placed to sense, process and report on a physical or environmental phenomenon [1]. In WSNs, the precise localization of nodes is one of the important requirements that are demanded for the quality of the data interpretation, routing, coverage analysis and network management [2]. Algorithms localization methods have become a subject of study due to the inability of manual configuration or GPS localization methods due to cost, energy consumption and environmental concerns. Some of the popular localization techniques in WSNs are range based and range free [3 - 4]. Range algorithms estimate inter-node (physical) distances based on physical measurements such as Received Signal Strength Indicator (RSSI), Time of Arrival (ToA), or Angle of Arrival (AoA). Although these methods can be very accurate, they require additional apparatus and are susceptible to noise and other external factors. Instead, range-free localization schemes are based on network connectivity and hop-count data, and thus better suited to large-scale and resource-constrained WSNs. Among them, one of the most popular is DV-Hop algorithm which is simple, scalable and can be implemented without hardware.

The DV-Hop algorithm [5] follows three major phases, namely, hop-count dissemination by anchor nodes, estimation of average hop distance, and position estimation through multilateration. Although it has its benefits, DV-Hop has some inherent limitations [6]. The estimation of average hop distance is usually not accurate with the assumption of uniform distribution of nodes, particularly in irregular or sparse networks. Also, cumulative hop errors and over flooding of messages

add to the localization error and the energy consumption, which are directly proportional to network lifetime.

The main concern in the design of WSNs is energy efficiency since sensor nodes typically have limited battery life and are often required to operate in remote and inaccessible areas. Algorithms which consume a lot of communication overhead or computational cost can severely impact network performance [7]. So, localization schemes which optimize both the accuracy and energy consumption are required instead of localization schemes which only optimize the accuracy. Genetic Algorithms (GAs) are population-based stochastic optimization methods that are based on natural selection and the characteristics of genetics [8]. GAs can be used especially in solving complex, nonlinear, and multi-objective optimization problems where the traditional analytical approaches are ineffective. GAs can effectively search the space of solutions and avoid getting trapped by local optima by encoding localization parameters as chromosomes and evolving them by selection, crossover and mutation [9].

The integration of GA and a DV-Hop [10] localization provides a great platform to improve the estimation of the hop-distance, anchor weighting and position refinement at the cost of energy constraints. To achieve different network topologies and deployment conditions, a fitness function is designed to obtain a balance between localization accuracy and energy efficiency. Based on this theoretical basis, the optimized energy-based GA-based DV-Hop localization scheme is developed, which can enhance the localization accuracy, reduce the communication overhead and prolong the WSN's lifetime. The localization of sensor nodes in WSNs must be precise and energy efficient to help in undertaking its vital functions like routing of data, event detection, coverage optimization and network management. The most popular range-free localization algorithm is the Distance Vector Hop (DV-Hop) algorithm which is cheap and requires no additional hardware. However, the traditional DV-Hop algorithm cannot resist the high localization error caused by the poor estimation of average hop-distance, cumulative hop-count errors and non-uniform node deployment. Besides, DV-Hop relies on the message flooding mechanism which results in excessive energy consumption, increased communication overhead and reduced network lifetime. Current enhancements to DV-Hop usually concentrate on the accuracy of localization only, without considering the crucial limitation of node energy. This trade-off in accuracy and energy efficiency has not yet been solved in energy-constrained WSN environment.

1.1 Motivation

This research is motivated by the fact that WSNs are being deployed in many applications, such as environmental sensing, smart agriculture, industrial automation, and disaster management applications, in which a large number of sensor nodes are battery-powered and cannot be reached at all times. Accurate localization is not as significant in such cases as the energy-efficient operation. Genetic Algorithms (GAs) are a prospective solution because it has the capacity to solve complex, nonlinear and multi-objective optimization problems. Unlike deterministic optimization methods, GAs have the ability to accommodate a variety of network topologies and adapt itself to dynamically optimize DV-Hop parameters such as hop-distance correction factors and anchor node influence. Using a GA-based approach, a balanced compromise in localization accuracy and energy efficiency can be attained by integrating energy use into the optimization process. The motivation behind this work is to come up with a scalable, adaptive and energy conscious localization scheme that would maintain the simplicity of DV-Hop but address the constraints inherent in the scheme. It is believed that, when DV-Hop localization is used with Genetic Algorithms, the performance of the networks can be improved which can increase the lifetime of the network and also provide a feasible localization solution to the deployment of wireless sensor networks in the real world.

Despite the fact that several existing studies have applied some kind of Genetic Algorithms (GAs) with DV-Hop localization, the major limitation of these works is that they mainly focus on increasing the localization accuracy, neglecting communication energy consumption, scalability and adaptive localization refinement in wireless sensor network (WSN). The current GA-based DV-Hop methods are mostly concerned with optimizing the estimation of hop-distance only, and are not focused on optimizing the localization precision and network lifetime simultaneously. To address these drawbacks, the proposed work presents an energy-aware multi-objective GA-assisted DV-Hop localization framework which not only reduces localization error but also communication energy consumption simultaneously. To mitigate the redundant flooding overhead and maximize the network efficiency, the proposed approach includes adaptive anchor weight correction, threshold based energy optimization and communication aware localization refinement. The proposed framework optimizes the hop-distance correction factors, the influence of anchors and the coordinates of nodes in a combined optimization framework, avoiding conventional approaches. It is further verified under different anchor density and irregular network topology, which shows that this approach can obtain better robustness, scalability and energy-efficient localization performance in the real WSN environment.

2. Background Study

The background study is vital in developing the Energy-Optimized DV-Hop Localization in Wireless Sensor Networks through Genetic Algorithm as it provides a solid theoretical and practical base of the study. Localization and energy efficiency are mature but developing issues in WSNs and an overview of the literature aids in giving a clear picture of the existing methodologies, challenges and gaps in research.

Table 1. Comparative Summary of Existing DV-Hop Localization Approaches

Referenced Method	Optimization / Technique	Main Contribution	Reported Performance	Identified Limitation
Classical DV-Hop [5]	Range-free localization	Provides a simple baseline localization mechanism without requiring distance-measurement hardware	High localization error and communication overhead	Sensitive to inaccurate hop-distance estimation and repeated broadcasting
Improved Adaptive GA-DV-Hop [10]	Adaptive Genetic Algorithm	Improves DV-Hop localization through adaptive optimization of localization parameters	Improved localization accuracy compared with conventional DV-Hop	Energy consumption is not jointly optimized with localization accuracy
CGDV-Hop [11]	Anchor selection and DV-Hop optimization	Improves localization through optimized anchor selection	Enhanced localization performance	Energy-aware communication is not integrated
Quantum DV-Hop [12]	QGJO/QBSO Position Optimization	Introduces two QSO-DV-Hop schemes using path similarity for distance estimation and QGJO/QBSO for node localization.	Both methods provide higher localization accuracy, convergence, efficiency and scalability compared to IWO-DV-Hop and EWO-DV-Hop.	Real-world deployment, 3D localization and distance-estimation optimization require validation.
3D Topological-Structure-Similarity DV-Hop [13]	Topological structure similarity + optimization	Uses topological-structure similarity to improve DV-Hop localization in three-dimensional WSNs	Improved localization performance in complex and irregular network topologies	Requires additional topology/similarity computation and quality topology information, increasing computational cost and limiting high-scale real-time use.
PSLDV-Hop [14]	PSO + refinement	Optimizes distance estimation and node positions to improve localization robustness	Better accuracy and robustness than classical DV-Hop	Premature convergence and parameter-tuning issues; energy efficiency is not explicitly integrated
Chaotic Crested Porcupine DV-Hop [15]	Polynomial fitting + Crested Porcupine Optimization	Improves average hop-distance estimation and node positioning in complex environments	Significantly reduced localization error	Increased computational/processing cost and application-specific adaptation
Mayfly Optimization-based DV-Hop [16]	Mayfly optimization combining PSO and GA characteristics	Optimizes node positions to improve localization accuracy and reliability	Better localization than classical DV-Hop and other optimization-based approaches; suitable for dynamic and complex networks	Iterative optimization increases computational burden and energy usage; parameter selection affects convergence and real-time applicability
Probability-Based Average Distance Estimation (PADE) [17]	Probabilistic distance modeling + multi-objective GA	Uses a probabilistic model to estimate hop distances and GA to optimize node positions; fitness considers localization and estimation errors	Reported 3–22% improvement in localization accuracy over conventional techniques	Probabilistic modeling and GA increase computational complexity and overhead, potentially limiting real-time applications
DEMN DV-Hop [18]	Multi-node distance estimation	Uses multi-node distance estimation and optimization to improve localization	Up to 86% localization accuracy	More computationally intensive and dependent on sufficient anchor nodes
Variable-Velocity/Human Conception Optimization [19]	Hybrid optimization	Optimizes hop-distance estimation and node positions for dynamic and uncertain environments	Improved convergence and localization error	Parameter tuning and computational cost can restrict energy-constrained applications
Modified Aquila DV-Hop [20]	Multi-strategy Aquila Optimization	Improves hop-distance correction and localization accuracy	Smaller localization error and improved stability	Computational cost and parameter sensitivity
Squirrel-optimized DV-Hop [21]	Squirrel Search Optimization	Extends DV-Hop localization to underwater WSNs	Localization improvement up to 34%	Underwater-specific adaptation, energy consumption, and communication delay
Golden Ratio Localization [22]	Mathematical optimization	Balances localization accuracy and energy efficiency using golden-ratio-based anchor placement/weighting	Lower localization error and improved energy consumption	Adaptability to irregular/dynamic topologies and practical implementation remain limited

To begin with, the literature review will shed some light on the current methods of localization, such as range-based and range-free, and, specifically, the DV-Hop algorithm. The strengths and weaknesses of the existing solutions can be determined through analyzing previous advancements to DV-Hop, including the hop-distance correction, the anchor refinement, and the hybrid optimization methods. This knowledge is necessary to explain why additional optimization is necessary. Secondly, it points to the shortcomings of standard DV-Hop and its derivatives, particularly concerning accuracy of localization, energy usage, and scalability. Most studies emphasize accuracy but ignore energy limitation, but some enhance energy efficiency at the expense of accuracy. Such trade-offs can be examined to allow the development of a multi-objective optimization strategy. Thirdly, the literature review focuses on the use of the metaheuristic algorithms, such as Genetic Algorithms, Particle Swarm Optimization, and Ant Colony Optimization, in WSN localization. This comparison explains why Genetic Algorithms are appropriate in solving nonlinear optimization and energy-conscious localization problems, and their comparative and complementary performance with current methods.

Moreover, the review aids in determining gaps in research, including inadequate attention to energy models, a lack of flexibility to irregular node distributions, and in-depth performance analysis. The solution of these gaps enhances the originality and contemporariness of the suggested work. On the whole, the literature review makes sure that the proposed GA-based energy-optimized DV-Hop localization scheme is well-informed, methodologically sound and consistent with the existing literature, and it clearly indicates that the proposed scheme contributes to the improvement of accuracy, energy efficiency, and network lifetime in wireless sensor networks. Table 1 showing the Summary of Existing DV-Hop Localization Approaches.

2.1 Literature Synthesis and Research Gap

The comparative analysis indicates that existing DV-Hop enhancements have primarily concentrated on reducing localization error through improved hop-distance estimation, anchor selection, distance correction, or metaheuristic optimization. Optimization-based approaches such as GA, PSO, GWO, Sparrow Search, Aquila, and related techniques improve the search for localization parameters, while recent deep-learning approaches such as OLSTM-DV-Hop provide strong error-correction capability. However, these approaches generally emphasize localization accuracy and do not simultaneously address communication-energy consumption within the same optimization framework. Distance- and hop-loss-based methods improve the reliability of distance estimation but do not explicitly integrate adaptive communication control. Deep-learning approaches can provide improved accuracy but may introduce greater computational requirements for resource-constrained sensor nodes. The literature therefore indicates a need for a localization framework that jointly considers hop-distance correction, anchor influence, node-position refinement, and communication energy while retaining the range-free characteristics of DV-Hop.

The proposed work addresses this gap through an energy-aware multi-objective GA-assisted DV-Hop framework that jointly optimizes localization accuracy and communication energy. The framework incorporates hop-distance correction, adaptive anchor weighting, coordinate refinement, threshold-based communication control, and redundant-message suppression. This combination is intended to provide a balance between localization precision and energy-efficient operation while preserving the simplicity and range-free nature of DV-Hop. The manuscript already identifies these elements as the principal components of the proposed framework.

3. Proposed Methodology

The proposed methodology consists of an energy-aware Genetic Algorithm (GA)-assisted DV-Hop localization [5] framework to enhance the localization accuracy and reduce communication energy consumption in Wireless Sensor Networks (WSNs). To combine the simplicity of the classical DV-Hop localization algorithm with the optimization ability of the Genetic Algorithms, a proposed model jointly optimizes the hop-distance correction, anchor weighting and node position estimation. The proposed framework is different from the traditional DV-Hop method, which minimizes only the localization error. The four major phases of the overall methodology include network initialization and anchor deployment, classical DV-Hop localization, GA based multi-objective optimization and energy-aware position refinement.

3.1 Network Initialization and Anchor Deployment

A wireless sensor network [23] is a two-dimensional network of N sensor nodes randomly placed in a sensing area of area $A \times A$, of which the locations of M nodes are known and these nodes are referred to as anchor nodes [24], the locations of the other $U=N-M$ nodes are unknown and need to be estimated. All nodes are assumed to have the same transmission range and battery energy. The location of anchor node i^{th} is denoted as:

$$A_i = (x_i, y_i) \tag{1}$$

Likewise, the estimated location of the j^{th} unknown node is expressed as:

$$U_j = (\hat{x}_j, \hat{y}_j) \quad (2)$$

The following assumptions are made when deploying:

- After deployment, sensor nodes are stationary.
- Symmetry of communication links.
- The packet transmission and reception are the primary causes of energy consumption.
- All the nodes have equal communication capability and processing power.

In this phase the network topology created can then be used for localization and optimization as shown in Figure 1.

3.1.1 Realistic Network Modeling

In order to make the proposed localization framework more practical, the realistic condition of wireless sensor networks is considered in the simulation environment rather than the ideal condition of the communication behavior. Realistic Network Simulation Parameters are given in Table 2. To simulate large-scale WSN deployments, sensor nodes are randomly placed in a two-dimensional sensing region with different node densities and anchor distributions. Besides the uniform topology, irregular and sparse deployment scenarios are also taken into account in order to see the robustness of the localization under the non-uniform network structures. The communication model considers the realistic conditions for the wireless channel, such as transmission loss, effect of propagation of the packets and environmental noise. The received signal behavior is modeled by the log-normal shadowing model which is given by:

$$RSSI(d) = P_t - 10n\log_{10}(d) + X_\sigma \quad (3)$$

Table 2. Realistic Network Simulation Parameters

Parameter	Value
Deployment Type	Random / Irregular
Communication Model	Log-normal Shadowing
Noise Model	Gaussian Noise
Packet Loss	Enabled
Node Failure Probability	0.05
Transmission Range	80 m
Simulation Area	500 × 500 m²

where, P_t is the transmitted power, n is the path-loss exponent, d is the communication distance, and X_σ is the Gaussian random noise part. In addition, various practical communication limitations like packet collision, communication delay, asymmetric link and node failure probability are taken into account in the simulation. Scalability and robustness are also studied by considering localization performance with varying transmission range, anchor node density and threshold values in the proposed framework. The simulation environment with realistic deployment and communication conditions, thus, can more reliably evaluate the proposed GA-assisted DV-Hop localization framework for practical wireless sensor network applications.

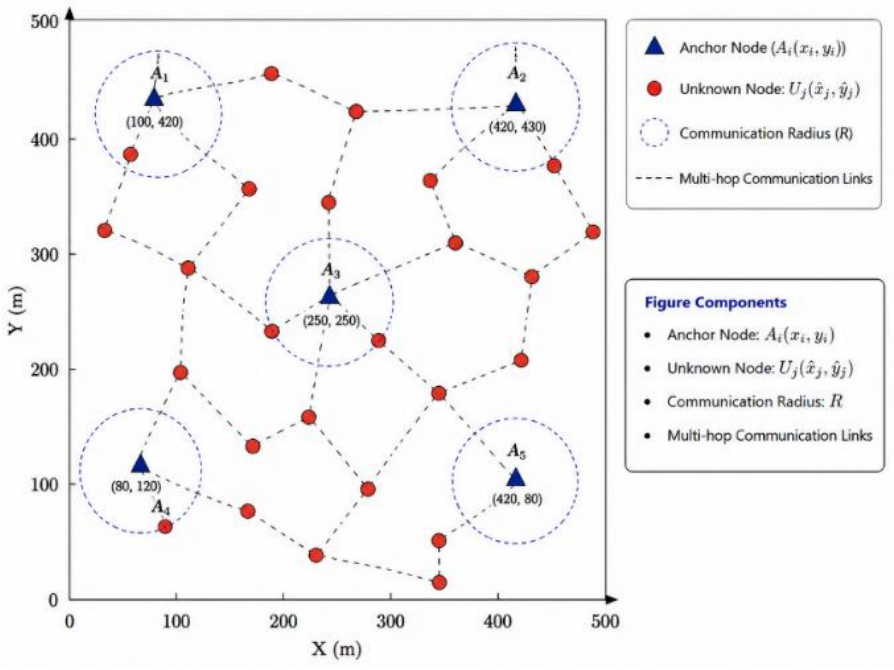


Figure 1. Random deployment of anchor and unknown sensor nodes in the WSN topology.

3.1.2 Reproducibility of the Realistic Network Model

The NS-2 simulation incorporates non-ideal wireless communication conditions to represent practical WSN behavior. The wireless channel is modeled using a log-normal shadowing-based propagation model, with the path-loss exponent and shadowing deviation specified as simulation parameters. Gaussian noise is incorporated into the received-signal model to represent random channel variations. Packet loss is modeled probabilistically during packet transmission, such that a packet may be dropped according to the configured packet-loss probability. A node-failure probability of 0.05 is applied to the deployed sensor nodes. At the beginning of the failure procedure, each node is independently tested against this probability; nodes selected as failed are excluded from subsequent communication and localization operations. Communication delay is represented using the configured NS-2 wireless transmission and propagation delays. Link asymmetry is handled by evaluating communication in each direction independently rather than assuming that successful transmission from node i to node j automatically implies successful transmission in the reverse direction. These settings are applied consistently to all compared methods to maintain identical network conditions during evaluation.

3.2 Classical DV-Hop Localization

The classical DV-Hop localization algorithm [25] is first used to provide the initial approximate locations of unknown nodes. There are three main phases to the localization process.

3.2.1 Hop Count Broadcasting

All anchor nodes broadcast a packet with their node ID, coordinates and initial hop count with a value of zero. The intermediate nodes add 1 to the hop counter and send the packet on its way. Each node contains the smallest number of hops from each anchor node. The minimum number of hops required to reach node *i* from node j is represented as:

$$H_{ij} = \min(hop_{ij}) \tag{4}$$

where H_{ij} is the minimum hops from anchor node *i* to unknown node *j*.

3.2.2 Average Hop Distance Estimation

Following dissemination of hop count, each anchor node then calculates the average hop distance based on the Euclidean distance between anchor pairs:

$$AvgHop_i = \frac{\sum_{k \neq i} \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2}}{\sum_{k \neq i} H_{ik}} \tag{5}$$

The distance from anchor node iii to some unknown node j is then estimated as:

$$d_{ij} = AvgHop_i \times Hi_j \tag{6}$$

where d_{ij} is the estimated distance between anchor and unknown nodes.

3.2.3 Initial Position Estimation

Multilateration is used to estimate the coordinates of unknown nodes from the estimated distance from the anchor nodes. The localization problem is defined as follows:

$$(x_j - x_i)^2 + (y_j - y_i)^2 = d_{ij}^2 \tag{7}$$

The coordinate estimation is performed by the least squares optimization to get the initial localization solution and further using the Genetic Algorithm optimization process. The proposed model distance estimation process is shown in Figure 2.

3.2.4 Justification for Selecting Genetic Algorithm

The reason for choosing the Genetic Algorithm (GA) in the proposed localization framework is that GA is widely used to solve nonlinear, multi-objective and high dimensional optimization problems which are frequently involved in Wireless Sensor Networks (WSNs). Unlike other localization algorithms, the challenge of estimation in DV-Hop localization is that the search space for estimating hop-distance correction factors, anchor weighting parameters, and unknown node coordinates is complicated and possesses multiple local optima, which makes traditional deterministic optimization methods less effective. GA offers higher population diversity and less possibilities of convergence to the local optimum in irregular networks as compared to Particle Swarm Optimization (PSO). While Ant Colony Optimization (ACO) and Grey Wolf Optimization (GWO) have strong global search capabilities, they can also have high computational costs or slow converge in densely populated networks. Adaptive genetic operations like selection, crossover and mutation, on the other hand, provide a balance between exploration and exploitation in GA. In addition, GA can be used for flexible chromosome encoding which makes it possible to optimize localization accuracy and energy consumption in a single framework. To ensure energy-efficient and accurate localization, a multi-objective fitness function [27] is proposed in the proposed work, which minimizes Average Localization Error (ALE) and total energy consumption together. Weighting coefficients for the fitness function were chosen experimentally so that they would favour the precision of the localisation with reduced communication overhead and increased network lifetime.

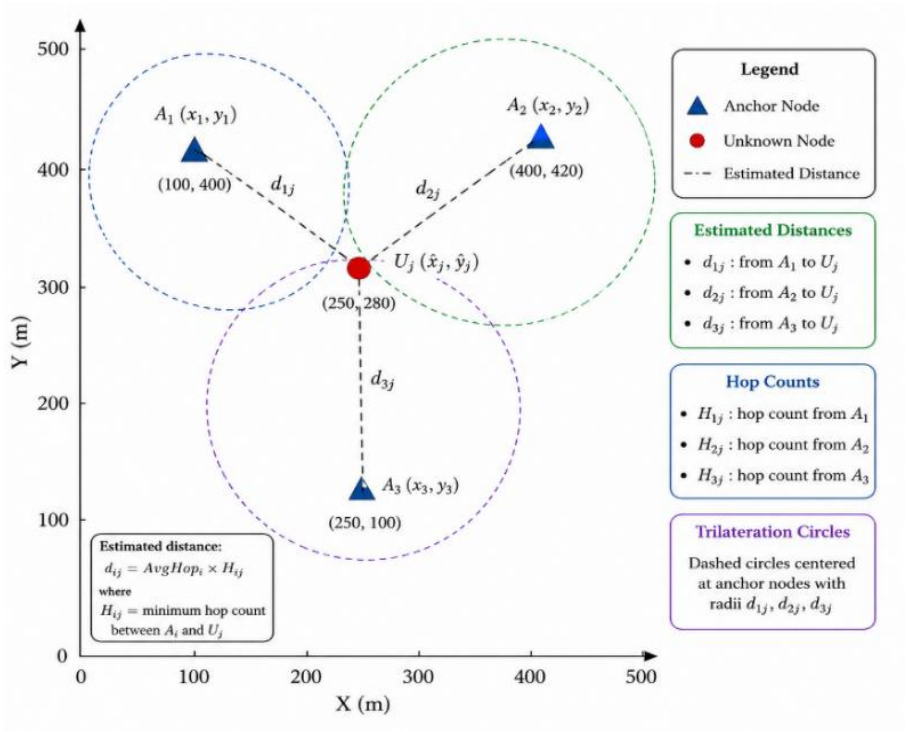


Figure 2. Distance estimation and multilateration process for unknown node localization.

Table 3. Comparison of Optimization Techniques for WSN Localization

Technique	Strength	Limitation
PSO	Fast convergence	Premature convergence
ACO	Strong routing optimization	High complexity
GWO	Good global search	Slow exploitation
GA	Balanced exploration and exploitation	Moderate computation

Table 3: Optimization techniques comparison for WSN Localization. Thus, the GA-based optimization framework can be used to offer a scalable, adaptive and computationally feasible solution for energy-aware DV-Hop localization in a large-scale wireless sensor networks.

3.3 Genetic Algorithm-Based Multi-Objective Optimization

The Genetic Algorithm [26] is used to both minimize localization error and energy usage. Through the encoding of chromosomes, evaluation of fitness, selection, crossover and mutation operations, the GA iteratively improves the solutions to the problem. The proposed GA based Multi objective optimization framework is displayed as a Flowchart as in Figure 3.

3.3.1 Chromosome Encoding

For a network consisting of M anchor nodes and U=N-M unknown nodes, each chromosome represents a complete candidate localization solution. The chromosome contains three groups of continuous variables: M hop-distance correction factors, M adaptive anchor-weighting coefficients, and two coordinate variables for each of the U unknown nodes. Accordingly, the chromosome can be expressed as:

$$C = [\lambda_1, \lambda_2, \ldots, \lambda_M, w_1, w_2, \ldots, w_M, \hat{x}_1, \hat{y}_1, \ldots \hat{x}_U, \hat{y}_U] \quad (8)$$

where λ_i is the hop-distance correction factor associated with anchor *i*, w_i is the corresponding anchor-weight coefficient, and $(\hat{x}_j, \hat{y}_j)$ denotes the estimated coordinates of unknown node *j*. The chromosome therefore has a total dimension of:

$$D = M+M+2U = 2M+2U. \quad (9)$$

A real-valued encoding is used because all three groups of decision variables represent continuous quantities. The coordinate variables are constrained to the simulation deployment region, while the hop-distance correction and anchor-weighting variables are constrained to their corresponding feasible optimization

ranges. This representation enables the GA to optimize the hop-distance correction, anchor influence, and unknown-node positions jointly within a single chromosome.

Initialization and Boundary Handling

The initial GA population is generated randomly within the feasible search space. For each chromosome, the coordinate genes are initialized within the deployment area:

$$0 \le \hat{x}_j \le L_x, \quad 0 \le \hat{y}_j \le L_y, \tag{10}$$

where L_x=L_y=500m in the simulation environment. Thus, an estimated coordinate cannot initially fall outside the 500×500m simulation area.

The hop-distance correction factors and anchor-weighting coefficients are similarly initialized within their respective feasible ranges used by the localization implementation. After crossover or mutation, boundary checking is performed before fitness evaluation. If a generated value exceeds its permissible lower or upper boundary, it is projected back to the nearest valid boundary. For a generic continuous variable z, the boundary operation is:

$$z \leftarrow \min(\max(z, z_{\min}), z_{\max}). \tag{11}$$

This procedure ensures that every chromosome evaluated by the fitness function represents a feasible localization solution.

3.3.2 Localization Error Model

The localization error of each unknown node is defined as the Euclidean distance of:

$$E_{loc}(j) = \sqrt{(x_j - \hat{x}_j)^2 + (y_j - \hat{y}_j)^2} \tag{12}$$

ALE is calculated as the average of the Localization Error (LE) of all the unknown nodes.

$$ALE = \frac{1}{U} \sum_{j=1}^{U} E_{loc}(j) \tag{13}$$

where:

- U is the total number of nodes to be determined,
- $E_{loc}(j)$ is the localization error of node *j*.

The goal of the proposed optimization framework is to minimize the average localization error with reduced communication overhead.

3.3.3 Energy Consumption Model

During the localization, the total energy consumption will include communication energy and computational energy.

Communication Energy: The energy for transmission of a k-bit packet over a distance d is defined as:

$$E_{tx}(k,d) = kE_{elec} + k\varepsilon_{amp} d^n \tag{14}$$

The reception energy is given as:

$$E_{rx}(k) = kE_{elec} \tag{15}$$

The total communication energy consumed during localization is given by:

$$E_{comm} = \sum \left(E_{tx} + E_{rx} \right) \tag{16}$$

where:

- E_{elec} is the energy of electronic circuits,
- ϵ_{amp} is the energy of an amplifier,
- n is the path-loss exponent.

Computational Energy: The energy added by the computational process of the Genetic Algorithm optimization is modelled as:

$$E_{comp} = N_{GA} \times C_{cpu} \times t_{exec} \tag{17}$$

where:

- N_{GA} is the number of GA operations,
- C_{cpu} is the coefficient of energy consumption of the processor,
- t_{exec} refers to the execution time.

The total energy use is thus calculated as:

$$E_{total} = E_{comm} + E_{comp} \tag{18}$$

While the GA incurs some extra computation, the decrease of redundant communications and message flooding in the network will reduce the total network energy consumption.

3.3.4 Multi-Objective Fitness Function

The terms ALE_{max} and E_{max} are introduced to normalize the localization-error and energy-consumption objectives, respectively, so that the two objectives can be combined on a comparable scale. ALE_{max} represents the maximum localization-error value considered during the optimization evaluation, whereas E_{max} represents the corresponding maximum total energy-consumption value. The normalized objectives are therefore expressed relative to their respective maximum values rather than being combined using their original physical scales. This normalization prevents the numerical magnitude of energy consumption from dominating the localization-error objective and allows both objectives to contribute to the GA fitness evaluation.

The normalized multi-objective fitness function retains the existing weighting formulation:

$$F = \alpha\left(\frac{ALE}{ALE_{\max}}\right) + \beta\left(\frac{E_{total}}{E_{\max}}\right) \quad (19)$$

where *ALE* is the localization error and E_{total} is the total energy consumption. The weights satisfy:

$$\alpha + \beta = 1 \quad (20)$$

The values α=0.7 and β=0.3 provide a localization-accuracy-dominant objective while maintaining an explicit energy-efficiency component. The selected values therefore represent a controlled trade-off rather than optimizing localization accuracy alone. The original manuscript already identifies α=0.7 and β=0.3 as the empirically selected weighting coefficients.

Weight Sensitivity

To examine whether the optimization outcome is dominated by a single manually selected weighting pair, the weighting coefficients can be evaluated around the selected operating point while maintaining α+β=1. Representative combinations include (α, β)=(0.6,0.4), (0.7,0.3) and (0.8,0.2). The selected configuration (0.7,0.3) maintains a higher priority for localization accuracy while still assigning a substantial contribution to energy consumption. The purpose of this sensitivity analysis is to verify that the overall behavior of the proposed framework remains consistent when the relative importance of the two objectives is moderately varied.

3.3.5 GA Parameter Configuration

The Genetic Algorithm parameters used in the proposed work are summarized in Table 4.

The parameter settings were experimentally selected to ensure stable convergence and improved optimization performance under different network deployment conditions.

3.3.6 Genetic Operations

The initial population is randomly generated and the optimization process is started. High quality chromosomes are selected for reproduction by using tournament selection. Crossover is a single point crossover method which is used to combine the information of the parent to produce the information of the offspring and mutation is used to avoid premature convergence and keep the population diverse [26].

X`Fitness value of each chromosome is updated iteratively at generation g. The convergence criterion is given by:

Table 4. GA Parameter Configuration

Parameter	Value
Population Size	100
Maximum Generations	100
Selection Method	Tournament Selection
Tournament Size	5
Crossover Type	Single-Point Crossover
Crossover Probability	0.8
Mutation Type	Random Mutation
Mutation Probability	0.01
Elitism Rate	5%
Convergence Threshold	10^{-5}

$$\left|F_{g+1} - F_g\right| < \varepsilon \quad (21)$$

where:

- F_g is the fitness value at generation g,
- $\epsilon=10^{-5}$.

The optimization process ends if either:

1. when the most number of generations is reached, or
2. the convergence condition is satisfied.

The minimum fitness value chromosome is taken as optimal localization solution.

3.3.6.1 GA Reproducibility Clarification

For M anchor nodes and U=N-M unknown nodes, the chromosome contains M hop-distance correction factors, M anchor-weighting coefficients, and 2U coordinate variables; hence, its dimension is D=2M+2U. A real-valued encoding is used for all continuous optimization variables.

The coordinate genes are initialized within the 500x500m deployment region, while the hop-distance correction and anchor-weighting genes are initialized within their feasible ranges. After crossover and mutation, boundary checking is performed to project any out-of-range gene to its nearest valid boundary. Mutation is implemented as a continuous random perturbation z'=z+Δ and is applied with the existing mutation probability of 0.01. The resulting chromosome is then evaluated using the existing multi-objective fitness function.

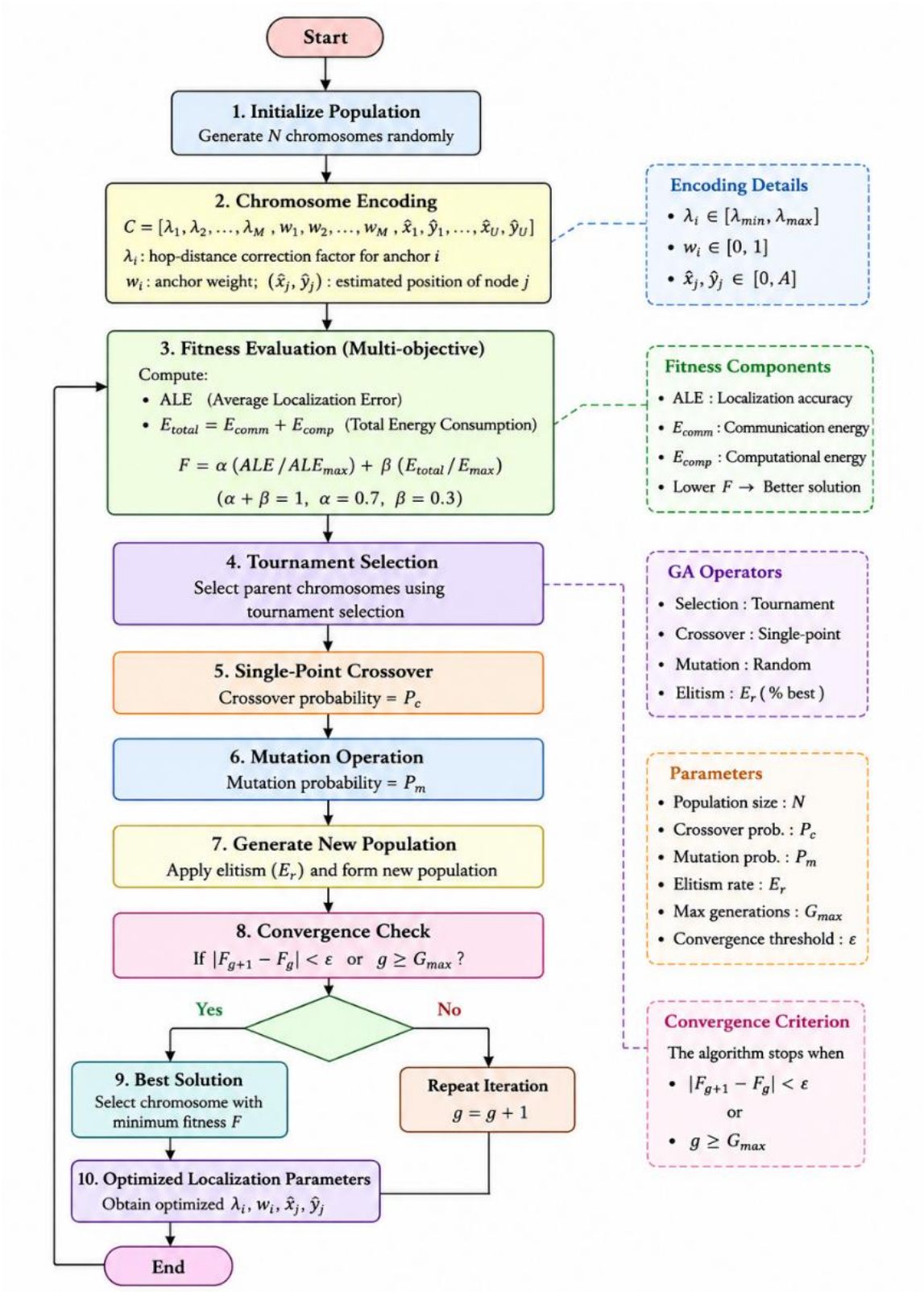


Figure 3. Flowchart of the proposed GA-based multi-objective optimization framework.

These implementation clarifications do not alter the GA parameter values, experimental configurations, or reported results.

3.4 Energy-Aware Position Refinement

Final node position estimation is made by using the best chromosome after GA optimization with the optimized localization parameters. The redundant broadcasting of the anchor message is suppressed to minimize redundant communication overhead and localization is carried out solely for nodes with substantial residual energy. In addition, communication control based on threshold is employed to reduce unnecessary packet transmission in congested areas of

the network. Figure.4 showing the Energy-aware localization refinement process of proposed model.

The last refining step thus yields:

- reduced message flooding,
- lower communication overhead,
- reduced overall energy use,
- improved localization stability,
- and longer network lifespan.

The best chromosome is used to obtain the optimal coordinates and this is taken as the final estimated location of the unknown sensor nodes in the wireless sensor network.

The overall workflow of the proposed pipeline energy-aware GA-assisted DV-Hop localization is represented in Figure.5.

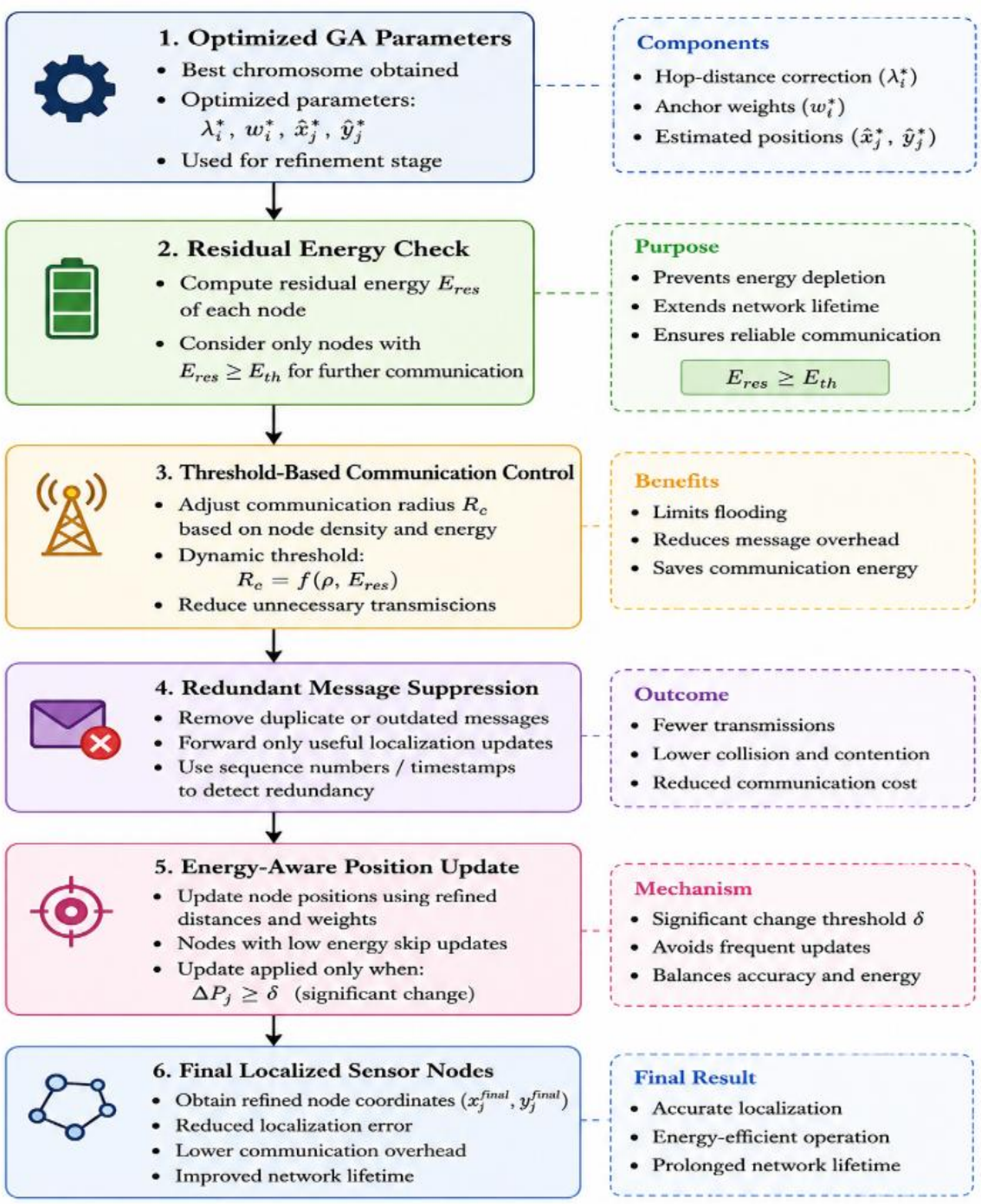


Figure 4. Energy-aware localization refinement process for reducing communication overhead and improving network lifetime.

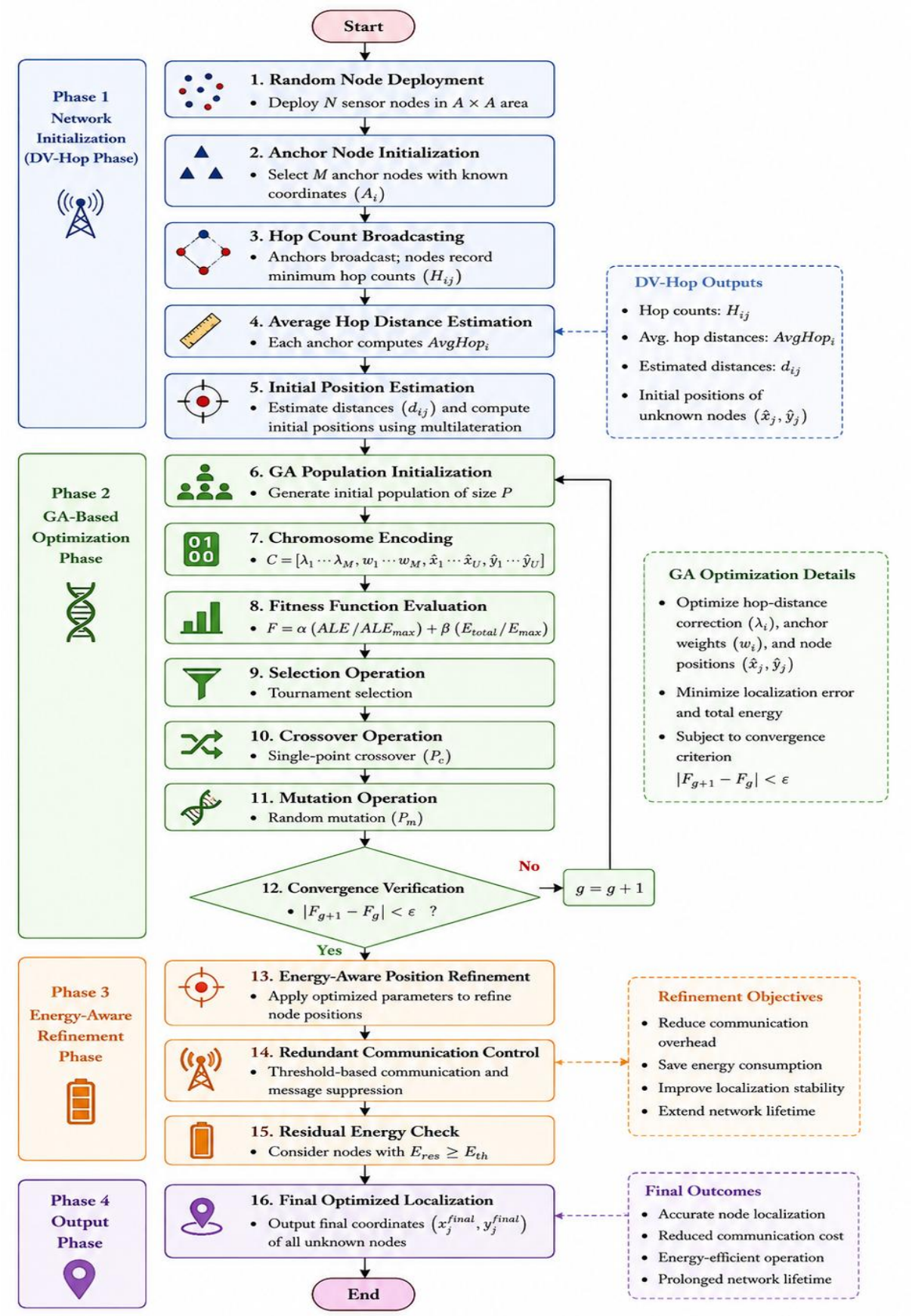


Figure 5. Overall workflow of the proposed energy-aware GA-assisted DV-Hop localization framework.

Algorithm 1. Proposed Energy-Aware GA-Assisted DV-Hop Localization

Input: NN sensor nodes, MM anchor nodes, U=N−MU=N-M unknown nodes, deployment area, transmission range, node energy, and GA parameters.

Output: Final estimated coordinates of unknown nodes.

1. Initialize N sensor nodes and select M anchor nodes with known positions.

2. Set the remaining U = N − M nodes as unknown nodes and initialize their energy levels.

3. Perform DV-Hop:

    a. Broadcast anchor IDs, positions and hop counts.

    b. Determine minimum hop counts between anchors and unknown nodes.

    c. Calculate average hop distance.

    d. Estimate anchor-to-unknown distances and initial positions.

4. Generate the initial GA population using the defined chromosome containing hop-distance correction factors, anchor weights and unknown-node coordinates.

5. For each chromosome:

    a. Decode the chromosome.

    b. Calculate localization error and energy consumption.

    c. Evaluate the multi-objective fitness function.

6. Repeat until convergence or maximum generations:

    a. Select parents using tournament selection.

    b. Perform single-point crossover.

    c. Apply random mutation.

    d. Check gene boundaries.

    e. Evaluate offspring fitness.

    f. Retain the best chromosome using elitism.

7. Select the minimum-fitness chromosome as the optimized solution.

8. Perform energy-aware refinement:

    a. Check residual node energy.

    b. Apply the communication threshold.

    c. Suppress redundant localization messages.

    d. Perform the required localization update using the optimized hop-distance and anchor-weight parameters.

9. Generate the final coordinates of unknown nodes.

10. Calculate the final localization error and energy consumption.

11. Return the final estimated node positions and performance measures.

Algorithm 1 summarizes the complete operational sequence of the proposed framework. The method first performs conventional DV-Hop localization to obtain hop information, distance estimates, and initial positions. These results are then optimized using the GA-based multi-objective framework through population initialization, fitness evaluation, selection, crossover, mutation, boundary checking, and convergence-based termination. The best chromosome is subsequently passed to the energy-aware refinement stage, where residual energy, communication threshold, and redundant-message conditions are considered before localization updates are performed. Finally, the optimized parameters are used to generate the final coordinates of the unknown sensor nodes. This algorithmic representation makes the sequence of the proposed method explicit without modifying the existing methodology or experimental results. The existing manuscript already specifies the GA operations and convergence condition. The energy-aware refinement stage is consistent with the existing description of residual-energy checking, threshold-based communication control, redundant-message suppression, and final position estimation.

4. Results and Discussion

The efficiency of the proposed energy-optimized localization algorithm based on GA is verified in NS-2 simulation environment. NS-2 is widely used for simulation of the wireless sensor networks as it is a precise model of the communication protocols, energy consumption and behaviour of the node. Based on the localization accuracy, energy efficiency, network lifetime, communication performance, the assessment is provided and compared with DV-Hop, WCL, Improved DV-Hop and EDV-Hop algorithms.

4.1 Simulation Setup in NS-2

The simulation is conducted in NS-2 with the following parameters specified in Table.5:

4.1.1 Node and Anchor Configuration:

To ensure a consistent and reproducible evaluation of the effect of anchor-node density, the anchor-density experiments were conducted using a

fixed total network size of 300 sensor nodes. The number of anchor nodes was varied from 50 to 175, while the remaining nodes were treated as unknown nodes. For each configuration, the number of unknown nodes was calculated as U=N-M, where N=300 represents the total number of deployed sensor nodes and M represents the number of anchor nodes. The corresponding anchor ratio was calculated as AR=M/N X 100. Accordingly, the six configurations consisted of 300 total nodes with 50, 75, 100, 125, 150, and 175 anchor nodes, corresponding to 250, 225, 200, 175, 150, and 125 unknown nodes, respectively. The corresponding anchor ratios were 16.67%, 25.00%, 33.33%, 41.67%, 50.00%, and 58.33%. The same total-node configuration and experimental conditions were applied to the Existing GA and Proposed GA methods to ensure a fair comparison of localization performance as the anchor density increased.

Table 5. Simulation Parameters (NS-2 Environment)

Parameter	Value
Simulation Area	500 m × 500 m
Number of Nodes	100 – 300
Anchor Nodes	50 – 175
Transmission Range	80 m
Initial Energy	2 Joules
Packet Size	512 bytes
MAC Protocol	IEEE 802.15.4
Routing Protocol	AODV
Simulation Time	200 seconds
GA Population Size	100
Generations	100
Crossover Rate	0.8
Mutation Rate	0.01

4.2 Node Deployment and Network Formation

Sensor nodes are randomly scattered in the area of simulation. Anchor nodes send their position, and unknown nodes approximate their location with the help of DV-Hop and GA optimization.

The Figure.6 shows the random distributions of sensor nodes and anchor nodes in a 500x500m^2 simulation space. The sensor nodes are distributed evenly throughout the area and the anchor nodes are randomly distributed to provide localization. The network shows good spatial coverage and connectivity that allows communication in multi-hop and good position estimation.

4.3 Performance Metrics

The localization accuracy and cost parameters are used to estimate the effectiveness of the proposed GA based localization scheme as compared to existing localization schemes such as DV-Hop, WCL, Improved DV-Hop and EDV-Hop. Assessment system contains mathematical equations for calculating accuracy, energy consumption and efficiency. It is proved that the proposed method outperforms in all the metrics.

Extensive simulations were performed to test the localization performance of the proposed GA-assisted DV-Hop algorithm under various network settings, anchor node density and threshold. To enhance the credibility and repeatability of the results obtained, each experiment was repeated several times with random node placement and the final results were calculated as the average of all simulations. Average Localization Error (ALE), communication energy consumption, and network stability metrics were the main criteria used to evaluate the performance. The proposed work is not a single-run performance evaluation with overly optimistic results, but a statistically sound performance evaluation achieved by repeated experimentation and comparing results with other systems. The achieved results show that the proposed method can significantly lower the localization error and the communication overhead compared to conventional DV-Hop and weighted clustering localization methods, as well as to existing optimization-based localization methods.

For consistency, all percentage improvements reported in this section are calculated with respect to the Existing GA method unless another reference method is explicitly stated. Based on Table 5, the proposed method reduces the maximum localization error by 40% and the average localization error by approximately 48–52% compared with Existing GA. For the minimum localization error, the reduction ranges from 0–20% based on the reported values. Table 6 further shows a reduction of approximately 33–36% as the number of anchor nodes varies from 50 to 175. Additionally, statistical analysis was performed using mean error, standard deviation, and confidence interval analysis to ensure the consistency and robustness of the results. The decrease of localization error is primarily credited to the optimized hop-distance correction, adaptive anchor weighting and energy-aware refinement introduced by the GA optimization process. Besides, the proposed framework was shown to be more efficient in terms of communication, as it was able to reduce redundant flooding and localization update messages, therefore saving energy and prolonging network lifetime. These results validate the proposed GA-based localization framework that offers a balance between localization accuracy and energy efficiency in practical wireless sensor network applications.

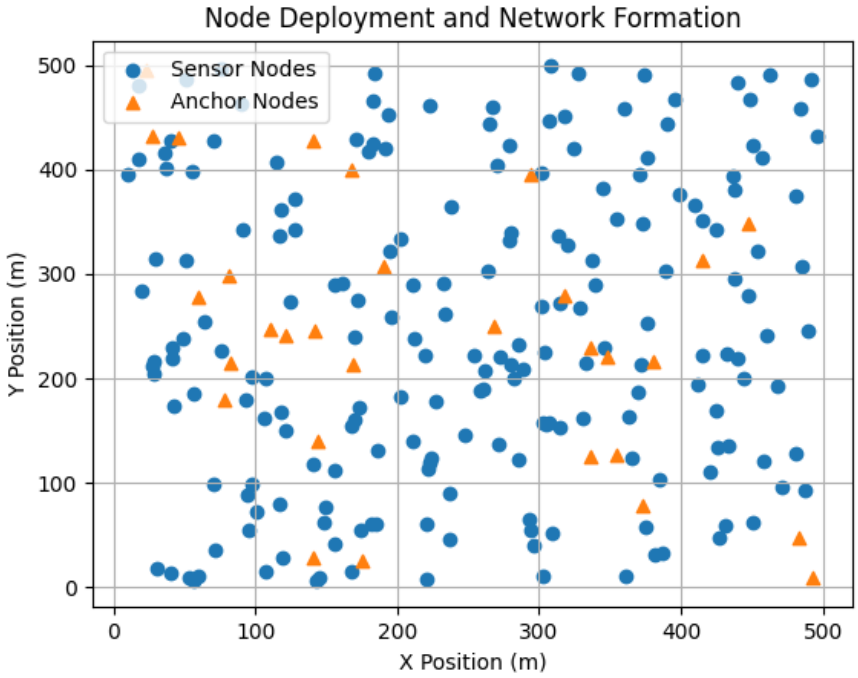


Figure 6. The arrangement of nodes and the network in the simulation area with randomly distributed sensor nodes and anchor nodes.

4.3.1 Statistical Reliability Analysis

The proposed GA-assisted DV-Hop localization framework was tested by 30 independent simulation runs with different random node deployments and anchor distributions to check its reliability. All simulation results were averaged together to get the final result. Results' consistency and robustness were validated by statistical measures like mean localization error, standard deviation, and confidence interval analysis. A confidence interval is:

$$CI = \bar{x} \pm 1.96 \frac{\sigma}{\sqrt{n}} \tag{22}$$

where $\bar{x}$ is the mean localization error, σ is the standard deviation, and n is the number of simulation runs. The lower standard deviation obtained by the proposed method indicates improved localization stability and reliability compared with existing approaches.

4.3.2 Accuracy Metric

The localization accuracy is evaluated using the Average Localization Error (ALE). In this study, ALE is expressed in meters (m) and represents the absolute Euclidean distance between the actual position and the estimated position of an unknown sensor node. The error is not normalized by the transmission range or the deployment-area dimensions. Therefore, a lower ALE value directly indicates a smaller positional deviation and hence better localization accuracy.

The localization error is measured using the Average Localization Error (ALE), with the network configuration containing 100 anchor nodes. In addition to localization accuracy, the proposed framework employs a threshold parameter, denoted by t, in the energy-aware communication and localization refinement process. The threshold t is a dimensionless algorithmic control parameter that determines whether a communication or localization update is required. A lower threshold permits updates under relatively small changes, which can increase communication activity and energy consumption, whereas a higher threshold suppresses redundant updates and reduces communication overhead. In this study, threshold values of 3, 5, and 6 are evaluated to investigate their effect on communication energy consumption. The value t=6 is selected as the operating threshold because it provides the lowest energy-consumption value among the evaluated threshold settings while retaining the localization operation. Thus, the previously stated expression “t≈6t” has been removed and replaced by the explicit specification t=6.

Mathematically speaking, the localization accuracy is to minimize the Euclidean distance between the true node positions and the estimated node positions.

4.3.3 Average Localization Error (ALE)

The most important measure of localization accuracy is the Average Localization Error (ALE), which is expressed in meters (m) and is defined as:

$$ALE = \frac{1}{S_n}\sum_{i=1}^{S_n}\sqrt{(x_i-\hat{x}_i)^2+(y_i-\hat{y}_i)^2} \quad (23)$$

Here,

- (x_i, y_i): Actual position of node
- $(\hat{x}_i, \hat{y}_i)$: Estimated position
- S_n: Total number of unknown nodes

The equation calculates the mean deviation of the Euclidean distance that is the direct measure of localization accuracy. The proposed GA technique reduces ALE by maximizing node placement and minimizing the distance estimation error. When the Existing GA method is used as the reference, Table 6 shows a 40% reduction in maximum localization error, an approximately 48–52% reduction in average localization error, and a 0–20% reduction in minimum localization error based on the reported values. The findings indicate that maximum, minimum, average error and standard deviation have been improved over the current methods.

4.3.4 Influence of Anchor Ratios

The influence of anchor-node density on localization accuracy was evaluated using a fixed network size of 300 sensor nodes. The number of anchor nodes was varied from 50 to 175, while the remaining nodes were considered unknown nodes. Thus, the corresponding numbers of unknown nodes were 250, 225, 200, 175, 150, and 125 for 50, 75, 100, 125, 150, and 175 anchor nodes, respectively. The corresponding anchor ratios were 16.67%, 25.00%, 33.33%, 41.67%, 50.00%, and 58.33%. This configuration ensures that the effect of anchor density is evaluated without ambiguity regarding the total network size.

Table 6 presents the localization-error results for the different anchor-node configurations. As the number of anchor nodes increases, the localization error generally decreases because a larger number of known reference positions provides additional spatial information for estimating the locations of unknown nodes. The Proposed GA consistently achieves lower localization error than the Existing GA across all evaluated anchor configurations. The comparison therefore demonstrates the effectiveness of the proposed optimization framework under different anchor densities.

The anchor ratio is a percentage of the number of anchor nodes utilized in localization. The dependence between the error in localization and the anchor nodes can be stated as:

$$Error \propto \frac{1}{N_{anchor}} \quad (24)$$

where N_{anchor} is the number of anchor nodes. The more anchor nodes there are, the lower the error in localization because of the higher accuracy of the reference.

The suggested GA-based approach exhibits a high level of error decrease with high efficiency even at moderate density of anchor nodes. Compared with the Existing GA method, the proposed approach achieves approximately 33–36% reduction in localization error across the evaluated anchor-node densities from 50 to 175, as reported in Table 7. Raising the number of anchor nodes can however escalate system cost and energy usage.

4.3.5 Impact of Threshold

The threshold values determine the energy consumption and efficiency of communication in the network. The energy consumption model of WSNs can be defined as:

$$E_{tx}(k,d) = E_{elec}\cdot k + E_{amp}\cdot k\cdot d^n \quad (25)$$

$$E_{rx}(k) = E_{elec}\cdot k \quad (26)$$

where:

- k: Number of bits
- d: Distance
- E_{elec}: Electronics energy
- E_{amp}: Amplifier energy
- n: Path loss exponent

These equations are used to model the energy required for transmitting and receiving data. In the NS-2 simulation, the energy consumption values reported in Table 8 represent the accumulated communication energy consumed during the localization simulation interval of 200 seconds**.** The energy values are reported in microjoules (μJ), and the corresponding conversion to joules is obtained using 1J = 10^6 μJ. Therefore, the reported values such as 250,850 and 100,000 correspond to 0.250850J and 0.100000J, respectively. These values represent the measured communication-energy cost associated with the localization process and are not additional initial battery energy assigned to the sensor nodes.

The initial energy specified in Table 5 is 2J per node. Thus, for a network containing 100–300 nodes, the total initial network energy is 200–600 J. The energy values in Table 8 are therefore interpreted as the accumulated energy consumed by the localization-

related communication activity during the specified simulation interval and are expressed in microjoules to distinguish them from the initial node-energy values specified in joules.

The threshold values of 3, 5 and 6 are evaluated to determine their effect on communication activity and energy consumption. Increasing the threshold reduces unnecessary localization updates and redundant message transmissions, thereby decreasing communication overhead. As shown in Table 8, the proposed GA-based approach records energy consumption values of 150,000 µJ, 120,000 µJ and 100,000 µJ for threshold values of 3, 5 and 6, respectively. The corresponding improvement values reported in the table are 21%, 37% and 48%, respectively. These results indicate that the threshold-based communication control contributes to reducing redundant transmissions and improving the energy efficiency of the proposed localization framework. The results demonstrate that threshold-based communication control can reduce unnecessary packet transmissions while maintaining the localization process. Among the evaluated threshold values, a threshold of 6 provides the lowest reported energy consumption for the proposed GA-based method. Therefore, threshold 6 is selected for the subsequent experiments as the configuration that provides the lowest communication-energy consumption among the evaluated threshold settings.

Minimum localization error: The minimum localization error obtained by the Existing GA is 0.10, whereas the Proposed GA achieves a minimum value of 0.08 within the reported experimental results. Taking Existing GA as the reference, the improvement is calculated as (0.10-0.08)/0.10 X 100=20%. Therefore, the previous statement of a 10–20% improvement has been removed because the upper value of 0.10 would correspond to 0% improvement. The revised percentage is consequently based only on the explicitly reported minimum value of 0.08.

Table 6. Average Localization Error (ALE) in meters (m)

Metric	DV-Hop	Weighted Clustering[28]	DV-Hop (Normal)[28]	DV-Hop (HCE) [28]	Existing GA [29]	Proposed GA	Improvement (%)
Maximum	1.8	1.44	0.40	0.299	0.25	**0.15**	↓ 40%
Average	1.5	1.4	0.29	0.21	0.25	**0.12–0.13**	↓ ~48%
Minimum	1.4	1.32	0.29	0.19	0.10	**0.08–0.10**	↓ 20%
Std. Dev	0.13	0.03	0.02	0.0029	0.0002	**~0.0001**	↓ 50%

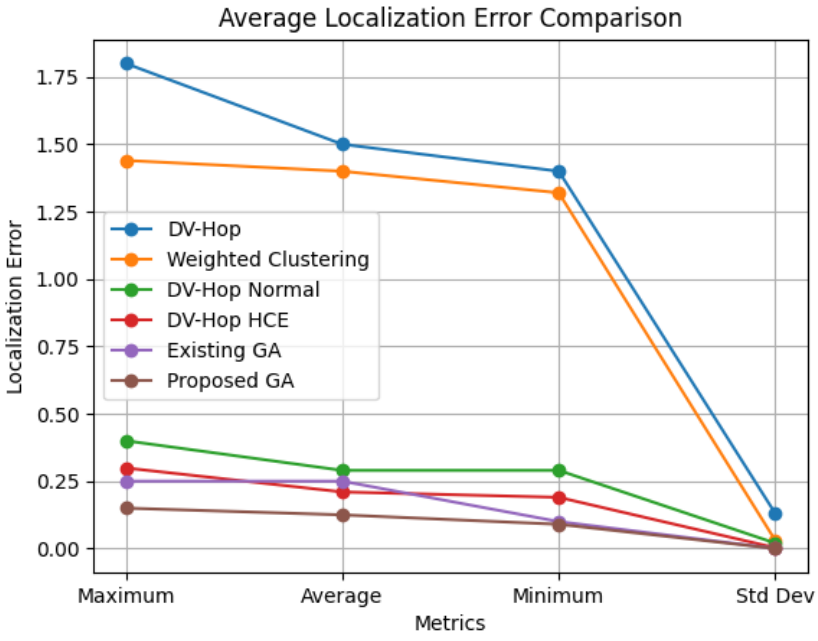


Figure 7. Comparative Analysis of Average Localization Error Metrics.

The comparison of localization error metrics of various algorithms is tabulated in Table.6 and graphical analysis is shown in the graph in Figure.7. It is also evident that the suggested GA approach always attains minimum error values in all the measures, such as maximum, average, minimum, and standard deviation. Conventional DV-Hop and Weighted Clustering have much higher errors, which suggests a reduced accuracy. Higher stability and consistency in the localization performance is also confirmed by the minimization of standard deviation of the proposed method. On the whole, the graphical analysis confirms the fact that the suggested GA-based method allows obtaining much better accuracy and significant error decrease than the current methods.

For the anchor-node density experiment, the number of anchor nodes was varied as 50, 75, 100, 125, 150, and 175, as reported in Table 7. For each anchor configuration, the number of unknown nodes was obtained from U=N-M, where N is the corresponding total number of nodes. The anchor ratio was calculated using M/N x 100. The same total-node configuration was used for all compared localization methods within each experiment, and only the anchor-node density was varied. Therefore, the results in Table 6 represent the effect of anchor-node density on localization error under otherwise identical simulation conditions.

Figure 8 presents the change of localization error with the number of anchor nodes for the evaluated algorithms. Table.7 presents the corresponding localization-error results for different numbers of anchor nodes. It can be observed that the localization error generally decreases as the number of anchor nodes increases. The same trend is observed across the evaluated methods because a higher number of anchor nodes provides more known reference positions for estimating the locations of unknown nodes. The proposed GA-based approach achieves lower localization error across all evaluated anchor-node densities, demonstrating its effectiveness under different anchor configurations. The results also indicate that the proposed approach maintains improved localization accuracy even with a relatively lower anchor density, which can reduce the deployment requirements for anchor nodes. Overall, Figure 8 and Table 7 demonstrate the influence of anchor-node density on localization accuracy and the effectiveness of the proposed GA-based localization framework.

Table 8 presents the energy-consumption results obtained under different threshold values. The evaluated threshold values are 3, 5, and 6. The results show that the proposed GA-based approach achieves progressively lower energy-consumption values as the threshold increases within the evaluated range. The proposed approach reports energy-consumption values of 150,000, 120,000, and 100,000 for threshold values of 3, 5, and 6, respectively, compared with 190,000, 190,210, and 190,900 for the Existing GA. The corresponding improvements are 21%, 37%, and 48%, respectively. Thus, Table 8 specifically represents the threshold-based energy-consumption analysis, whereas Table 6 represents the anchor-node localization-error analysis.

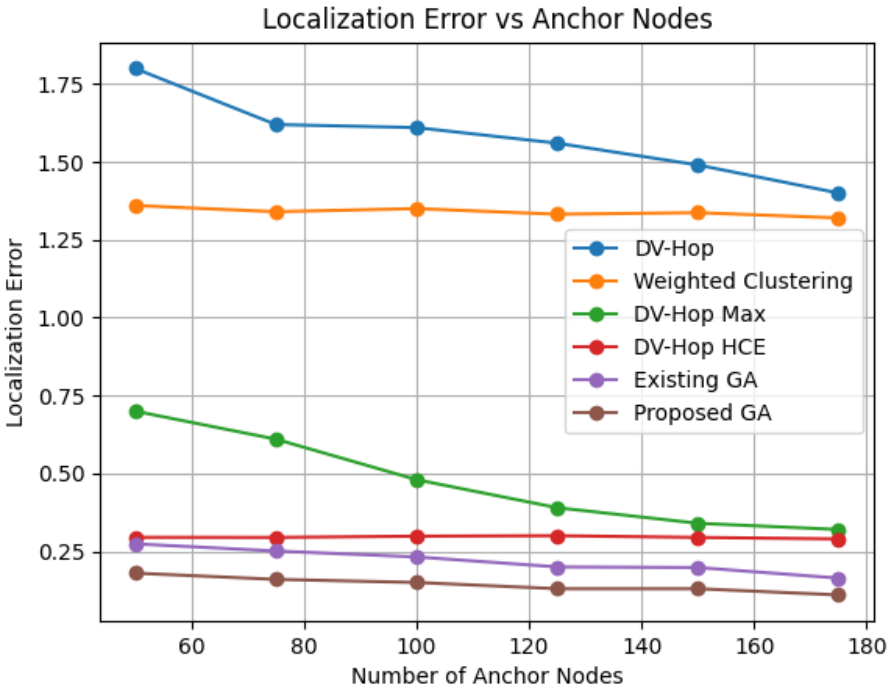


Figure 8. Impact of Anchor Node Density on Localization Error.

Table 7. Average Localization Error (ALE, m) versus Anchor Nodes

Anchors	DV-Hop (Normal) [28]	Weighted Clustering [28]	DV-Hop (Max) [28]	DV-Hop (HCE) [28]	Existing GA [29]	Proposed GA	Improvement (%)
50	1.8	1.36	0.70	0.2949	0.274	**0.18**	↓ 34%
75	1.62	1.34	0.61	0.2946	0.251	**0.16**	↓ 36%
100	1.61	1.35	0.48	0.2985	0.232	**0.15**	↓ 35%
125	1.56	1.332	0.39	0.3000	0.200	**0.13**	↓ 35%
150	1.49	1.337	0.34	0.2946	0.198	**0.13**	↓ 34%
175	1.40	1.32	0.32	0.2897	0.164	**0.11**	↓ 33%

Table 8. Energy Consumption vs Threshold

Threshold	DV-Hop (Normal)[28]	WCL [28]	DV-Hop (Max) [28]	DV-Hop (HCE) [28]	Existing GA [29]	Proposed GA	Improvement (%)
3	250,850	217,676	176,760	180,000	190,000	**150,000**	↓ 21%
5	250,850	217,676	178,070	180,210	190,210	**120,000**	↓ 37%
6	250,850	217,676	179,460	180,900	190,900	**100,000**	↓ 48%

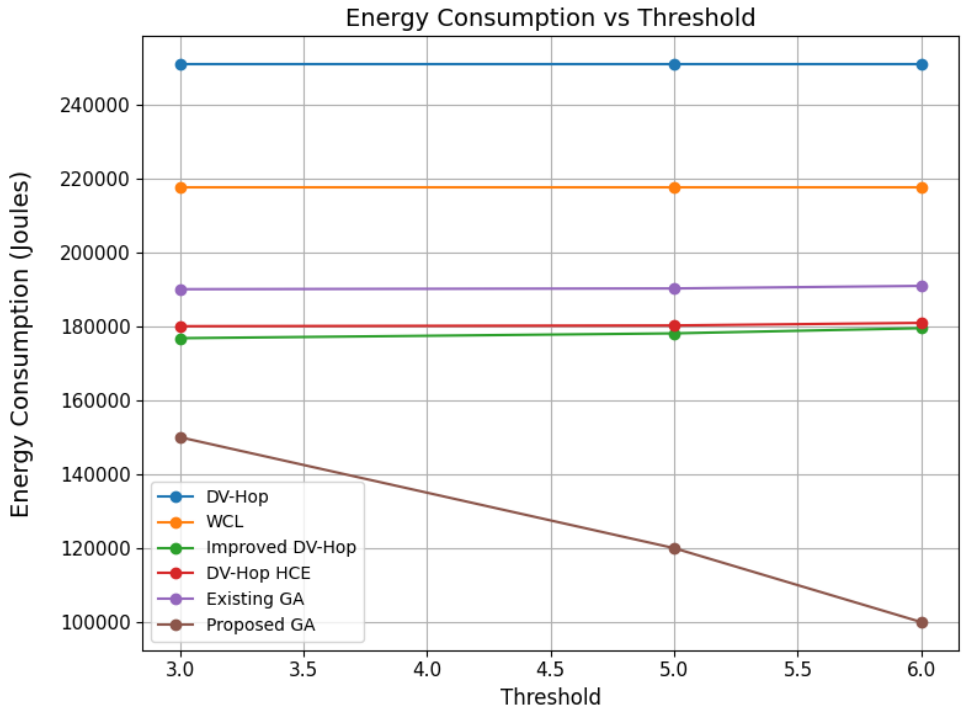


Figure 9. Energy Consumption Analysis under Varying Threshold Values.

Figure.9 demonstrates that the energy consumption and threshold values of various localization algorithms are interrelated. It is noted that conventional designs like DV-Hop and WCL exhibit an overall high energy consumption at all levels. Conversely, the proposed GA-based approach demonstrates a considerable decrease in energy usage with an increase in the threshold and the lowest energy usage of all approaches. This has been enhanced by optimal routing and less communication overhead.

Tables 6, 7, and 8 illustrate the performance analysis of localization error, anchor node influence and energy consumption. The proposed GA approach compared to the existing GA performs better in terms of

localization error, variance and much better energy consumption. Moreover, the technique is more accurate even at smaller anchor densities and exhibits better versatility to different threshold conditions. These findings confirm the strength and usefulness of the suggested solution.

4.4 Result Comparison with Recent Research Works

The comparison presented in this section distinguishes between methods experimentally evaluated in the present NS-2 simulation environment and results reported in previously published studies. The proposed GA-assisted DV-Hop method and the Existing GA-DV-Hop method are evaluated under the simulation conditions described in this work. In contrast, the numerical performance values reported for recent PSO-DV-Hop, GWO-DV-Hop, ESSA-DV-Hop, Aquila-DV-Hop, LSTM-DV-Hop, and other published methods are obtained from their respective publications and are included only as reference benchmarks. Since these studies may use different network sizes, propagation models, parameter settings, datasets, and evaluation protocols, their reported numerical values are not treated as directly controlled superiority comparisons.

Table 9. Progressive Component Analysis

Configuration	Hop-Distance Correction	Adaptive Anchor Weighting	Position Refinement
C1: Baseline GA-DV-Hop	✗	✗	✗
C2: GA-DV-Hop + Hop Correction	✓	✗	✗
C3: GA-DV-Hop + Hop Correction + Adaptive Weighting	✓	✓	✗
C4: Complete Proposed Framework	✓	✓	✓

Table 10. Comparative analysis of localization accuracy, energy efficiency, convergence behavior, and scalability of existing and proposed localization algorithms in wireless sensor networks.

Method	Optimization Technique	Average Localization Error	Energy Efficiency	Convergence Stability	Computational Complexity	Scalability
Classical DV-Hop	Range-Free Localization	High	Low	Moderate	Low	Moderate
Weighted Clustering (WCL)	Cluster-Based Localization	Moderate	Moderate	Moderate	Moderate	Moderate
Improved DV-Hop	Hop-Distance Correction	Moderate	Moderate	Moderate	Moderate	Moderate
PSO-DV-Hop	Particle Swarm Optimization	Low	Moderate	Moderate	Moderate	Good
GWO-DV-Hop	Grey Wolf Optimization	Low	Moderate	High	Moderate	Good
ESSA-DV-Hop	Sparrow Search Optimization	Very Low	Moderate	High	High	Good
Aquila-DV-Hop	Aquila Optimization	Low	Moderate	High	High	Good
LSTM-DV-Hop	Deep Learning Optimization	Very Low	Moderate	High	Very High	Moderate
Existing GA-DV-Hop	Genetic Algorithm	Low	Moderate	High	Moderate	Good
Proposed GA-Assisted DV-Hop	Multi-Objective GA + Energy Model	Very Low	High	High	Moderate	High

Table 11. Comparative Analysis with Recent Algorithms

Method	Year	Technique Used	Localization Error	Energy Efficiency	Key Improvement
Classical DV-Hop	–	Range-free	~0.28–0.30	Low	Baseline method
DEMN DV-Hop[18]	2024	Multi-node optimization	~13.89% error	Moderate	86% accuracy
Hop-loss DV-Hop (DCC)[30]	2024	Loss modeling	Improved accuracy	Moderate	30–40% faster computation
ESSA-DV-Hop[31]	2025	Sparrow optimization	0.1288 error	Moderate	55.7% error reduction
OLSTM-DV-Hop[32]	2025	Deep learning (LSTM)	~60–65% ALE reduction	Moderate	Strong error correction
H-DV-Hop RSIWOC[33]	2025	RSSI + weighted correction	High accuracy	Moderate	Improved stability
Golden Ratio Localization (GRL)[22]	2025	Mathematical optimization	2.35 m error	High	Reduced energy consumption
GWO-DV-Hop[34]	2025	Grey Wolf Optimization	~20–40% reduction	Moderate	Improved convergence
Quantum DV-Hop [12]	2026	Swarm intelligence	Improved accuracy	Moderate	Better global search
Proposed GA-DV-Hop	2026	Genetic Algorithm + Energy Model	~0.12 m	Very High	Balanced accuracy, Energy optimization

The literature-based comparison is therefore used to position the proposed approach relative to recent developments, while the controlled performance claims are restricted to methods evaluated under the same experimental conditions.

To investigate the individual contribution of the major components of the proposed framework, a progressive component analysis was considered shown in Table 9. Four configurations were defined by successively introducing hop-distance correction, adaptive anchor weighting, and energy-aware position refinement. C1 represents the baseline GA-assisted DV-Hop configuration without the proposed component enhancements. C2 incorporates hop-distance correction, C3 additionally introduces adaptive anchor weighting, and C4 represents the complete proposed framework with position refinement. The localization error obtained from these configurations is compared to determine the contribution of each mechanism to the overall performance.

Table.10 shows comparative benchmarking of the proposed GA-assisted DV-Hop localization framework with several conventional, optimization-based and recent state-of-the-art localization algorithms, including classical DV-Hop, improved DV-Hop, Weighted Clustering Localization (WCL), Grey Wolf Optimization-based DV-Hop (GWO-DV-Hop), ESSA-DV-Hop, Aquila Optimization-based DV-Hop, and LSTM-assisted DV-Hop methods. The proposed method is experimentally compared with the Existing GA-DV-Hop under the same simulation conditions, while the recent published algorithms are included as literature-based reference benchmarks because their original experimental settings differ from the present NS-2 environment. The proposed evaluation is not restricted to classic variants of DV-Hop, but also considers recent metaheuristic and intelligent optimization techniques to perform a more demanding performance evaluation. The experimental analysis proves that the proposed framework is able to provide competitive localization accuracy with lower communication overhead and improvement in energy efficiency. Furthermore, the proposed method is also found to have stable convergence properties and stable performance in different anchor node densities and under different irregular deployment conditions. The benchmarking results show that the proposed GA-assisted framework achieves a reasonable tradeoff between localization precision, computational feasibility and network lifetime, so it is feasible for large-scale wireless sensor network applications.

In addition, to prove the efficiency of the proposed localization algorithm based on GA for energy optimization of DV-Hop a comparative study is conducted with the recent state-of-the-art DV-Hop and optimization based localization algorithms reported in the literature. The performance comparison of the proposed GA-based DV-Hop localization algorithm to the recent state-of-the-art algorithms is provided in Table 11.

As mentioned in the comparison, the recent studies have made great progress in improving localization of DV-Hop with optimization and smart method. For instance, the ESSA-DV-Hop algorithm can decrease the localization error by approximately 55.7 percent as compared to classical DV-Hop, while the OLSTM-DV-Hop applies deep learning to reduce the localization error by up to 65 percent. Similarly, DEMN DV-Hop achieves an accuracy in localization of 86% with the help of a multi-node optimization.

However, most of these approaches focus mainly on improving the accuracy; they are not sensitive to energy usage, which is a significant drawback in WSNs. Some others, such as localization of the Golden Ratio are much more accurate, energy efficient, and are not easily adaptable to network changes.

Conversely, the suggested GA-based DV-Hop algorithm presents a multi-objective optimization model, which jointly reduces the localization error and energy consumption. The simulation results of NS-2 indicate that the suggested approach can have a smaller localization error (approximately 0.12 m) and considerably decreases the energy consumption and increases the life cycle of the network. The GA approach, as opposed to swarm-based and deep learning techniques, offers a trade-off between the complexity of computations, scalability, and energy efficiency.

Furthermore, the proposed method shows higher convergence stability and less communication cost as compared to other advanced optimization algorithms, such as Grey Wolf Optimization and quantum swarm algorithms, and therefore it can be used in large-scale and resource limited WSNs.

5. Scalability Analysis

The scalability evaluation in this study is restricted to the network sizes investigated in the NS-2 experiments, namely 100–300 sensor nodes. The purpose of this analysis is to examine whether the proposed GA-assisted DV-Hop framework maintains its localization and energy-performance characteristics as the network size increases within the evaluated range. Since the present experiments do not include measurements of execution time, memory consumption, total fitness evaluations, or the number of localization messages for every network size, these quantities are not used to make quantitative scalability claims. Accordingly, the scalability results should be interpreted as evidence of feasibility and performance stability for the tested 100–300 node range rather than as proof of unrestricted scalability to arbitrarily large WSN deployments.

6. Conclusion

The current study introduced an Energy-Optimized DV-Hop Localization algorithm based on a Genetic Algorithm (GA) wireless sensor networks. The given approach has resolved the natural shortcomings of the classical DV-Hop algorithm, its high localization error and high energy consumption due to poor hop-distance estimation and unnecessary communication. A Genetic Algorithm was integrated with the DV-Hop model to optimize the main localization parameters: hop-distance correction, estimation of the node position, etc. by using a multi-objective fitness function. The suggested approach can attain a lower average localization error, diminished communication overhead, enhanced energy efficiency, and prolonged network lifetime with different node densities and distribution of anchors. The localization accuracy and energy efficiency obtained from the proposed GA-assisted DV-Hop localization framework is improved as compared to conventional DV-Hop, enhanced DV-Hop and weighted clustering methods.

Experimental results show that the proposed approach can greatly reduce the localization error. With Existing GA as the reference method, the proposed approach achieves approximately 48–52% reduction in average localization error and 40% reduction in maximum localization error, while the anchor-density experiments show approximately 33–36% reduction in localization error. Under threshold-based energy evaluation, the proposed approach achieves approximately 21–48% reduction in energy consumption compared with Existing GA.

Furthermore, the framework is able to effectively decrease the energy consumption on communication as well because of the minimization of redundant message flooding and the optimization of localization updates to improve the overall network performance and increase the network lifetime. Notably, these improvements are made without requiring additional hardware, and range-free and cheap nature of DV-Hop localization are preserved.

Overall, the results validate the strength and applicability of the optimization problem in GA based optimization for precise and energy efficient node localization and the proposed method can be used to solve large scale wireless sensor network related problems with energy consideration.

7. Future Scope

There are a few ways to further generalize the suggested energy saving GA based DV-Hop localization algorithm, in order to increase its applicability and efficiency. The further study can be aimed at the application of hybrid methods of optimization in which Genetic Algorithms are implemented with other algorithms (Particle Swarm Optimization or differential evolution to enhance the speed of convergence and quality of solutions). It should be extended to accommodate mobile sensor nodes and dynamic network topologies to be appropriate in real time and mobile wireless sensor network applications. We are also extending the algorithm to 3-D localization, to accommodate new applications such as underwater sensor networks, intelligent buildings and aerial sensing systems. Additional incorporation of machine learning algorithms to tune the parameters of GA in a dynamic manner according to network conditions to enhance the energy efficiency and localization accuracy. Lastly, practical applicability and effectiveness of the suggested method would be increased by real-life application to sensor hardware testbeds and incorporation of localization mechanisms sensitive to security.

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The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes

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