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Research Article

Optimizing energy efficiency and enhancing localization accuracy in wireless sensor networks through genetic algorithms

P. Sakthi Shunmuga Sundaram[1] and K. Vijayan[2*]
Research Scholar, Department of Electronics and Communication Engineering, College of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, Chennai 603203, Tamil Nadu, India[1]
Associate Professor (Grade II), Department of Electronics and Communication Engineering, College of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, Chennai 603203, Tamil Nadu, India[2]

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Abstract
A wireless sensor network (WSN) is a dedicated wireless network designed to gather and transmit data from numerous compact sensor nodes dispersed across a defined geographical area. These sensor nodes are equipped with sensors, processing capabilities, and wireless communication abilities, working in concert to monitor and collect data from the surrounding physical environment. The practical implications of this research reverberate within the realm of WSN development, encompassing the exploration of energy-efficient protocols and strategies tailored to diverse real-world applications, ranging from commercial to agricultural contexts. Of paramount importance in WSN is the capability for precise location identification. This sought-after feature indicates the exigency for addressing multifaceted challenges linked to resource scheduling and the tracking of moving objects within the network's purview. The intrinsic energy limitations of individual nodes perpetuate the discontinuity and sparsity inherent in sensor data, accentuating the intricacy of network operations. The endeavor to identify and track objects continuously necessitates a strategic approach. The proposed method leverages genetic algorithm (GA) to craft a fitness function. This function encompasses the refinement of network energy residue, estimation of distances, and the scope of connection coverage. By embracing this methodology, energy conservation gains traction, leading to a pronounced augmentation in the lifespan of the WSN. The practical manifestation simulations were conducted using Spyder (Python 3.11). Notably, these results exhibit a remarkable 92% improvement in energy reduction when contrasted with alternative algorithms. This augmentation not only bolsters node location accuracy but also extends the network's temporal longevity. Moreover, the experimental outcomes underscore the error of unknown nodes, substantiating its proficiency in minimizing localization discrepancies. This research embarks on the intricate trajectory of WSN optimization. By harnessing the capabilities of GA, it navigates the terrain of energy consumption optimization, longevity extension, and accuracy enhancement. The consequential simulations affirm the potency of the proposed approach, paving the way for more refined and efficient WSN operations. The GA approach greatly improves localization accuracy, expedites tracking of unidentified nodes, ensures efficient anchor node support, and reduces energy consumption by 92% compared to other algorithms, all while maintaining high accuracy and minimal location errors in WSN.

Keywords
Energy efficient, Accuracy, Lifetime, Wireless sensor network, Localization error, Clustering, Genetic algorithm.

1.Introduction
A wireless sensor network (WSN) is a cutting-edge technology revolutionizing how we gather and process data in various applications. It is a network of small, autonomous devices called wireless sensors that can sense, collect, process, and transmit data over wireless communication channels.

To build the WSN the important key components are each sensor node is self-contained, typically comprising a sensing unit, processing unit, wireless communication module, and a power source. The sensors collaborate to form a distributed network that can efficiently monitor and report data from the environment they are deployed. In the wireless communication part, the WSN communicates using various wireless technologies like Wi-Fi, Bluetooth, Zigbee, or specialized low-power, long-range

*Author for correspondence

protocols like long-range wide area networks (LoRa WAN). The choice of communication technology depends on factors such as power consumption, data rate, transmission range, and application requirements. This gateway interfaces the WSN and external systems like the internet or data processing servers. Data processing and analysis after transmitting the data to the gateway, can process and analyze it to derive valuable insights and make informed decisions. They extract meaningful patterns and trends from the vast amount of network-generated data. WSN has found applications in various fields, including environmental monitoring. WSNs are used to monitor environmental parameters such as air quality, temperature, and humidity. They play a vital role in studying climate change and natural disasters. In industrial automation applications involved in industrial settings, WSN helps monitor machinery health, track inventory, and optimize production processes.WSN enables precision agriculture by monitoring soil moisture levels, crop health, and environmental conditions, which can lead to improved crop yields and resource management. WSN forms the backbone of smart city initiatives, facilitating intelligent traffic management, waste management, and energy efficiency. the research proposes a range-free localization scheme utilizing received strong signal (RSS) measurements. This limitation can also impact the scalability of the network. Wireless communications in WSNs are susceptible to interference from other wireless devices and environmental factors such as walls, buildings, and foliage, resulting in signal attenuation and potential data loss. WSNs are often deployed in dynamic environments [1]. By conducting evaluations under different environmental noise conditions, the researchers ensure a more realistic and thorough assessment of the proposed algorithms' effectiveness and suitability for practical implementations in WSNs [2]. WSN is utilized in healthcare for remote patient monitoring, tracking medical assets, and providing real-time data to healthcare professionals. Bio-inspired algorithms are utilized for their ability to converge to high-quality solutions quickly. Specifically, the focus is on distributive localization, addressed using two bio-inspired algorithms. The comprehensive learning particle swarm optimizer algorithm achieves a higher accuracy of 80.478% in localizing the nodes, while the particle swarm optimization (PSO) algorithm achieves an accuracy of 61.48% [3]. The development and adoption of WSN have opened new possibilities in various sectors, offering unparalleled data collection, monitoring, and analysis capabilities. As technology evolves, WSNs are expected to become even more sophisticated, efficient, and pervasive, contributing to a smarter and more connected world. As a type of defense in depth, identifying maladaptive devices on the network is a common and widely used security strategy in various computing disciplines. To produce useful data, the main hurdle in anomaly detectors must be adjusted to produce as few errors as possible. It can be difficult to modify known security best practices to work with the unique internet of things (IoT) computing paradigm. The goal is to reduce the incidence of either flagging positive behavior or not reporting malicious activity [4]. The principal application in remote sensor networks is executed in planned operations administrations. WSNs are utilized in two climates: underwater and earthbound. It is utilized for limitation reasons that imply detecting and tracking at a low cost. Fundamentally, this is attributable to how, in an interior environment, exact findings in the event of unembellished multi-path blurring often require an enormous measure of static node detection in the region. Nature-inspired algorithms like flower pollination algorithm (FPA), firefly algorithm (FA), grey wolf optimizer (GWO), and PSO are analyzed for localization in WSNs based on three key metrics: localization accuracy, localized nodes, and computing time. The goal is to identify the best algorithms that achieve high accuracy, minimize uncertain nodes, and offer fast computation. This contributes to WSN advancement in environmental monitoring, industrial automation, agriculture, and smart cities, enabling informed algorithm selection for a connected and data-driven world [5]. Multilateral advanced and multidimensional scaling (MA-MDS) is a robust localization algorithm for WSNs that effectively reduces error accumulation in multilateral positioning and improves the accuracy of sensor node localization, particularly in noise-sparse networks with fewer anchor nodes. By combining the strengths of the two approaches, provides a valuable contribution to WSN localization techniques, enabling more reliable and accurate data collection [6]. Decreasing the nodes reduces the expense, and the high number of nodes will be removed, smaller than exactness [7]. The authors emphasized that their refined algorithm is tailored to address the specific challenges of detecting and tracking vehicles in large areas where continuous monitoring is critical. The proposed approach presents a comprehensive solution for precise vehicle tracking, contributing to more effective and reliable vehicle surveillance and monitoring applications [8]. Collecting more anchor nodes implies higher position exactness in a more extensive range. Be that as it may, the prize of a node is high, and the anchor node prize is higher than the normal nodes [9]. The WSN is depicted in the diagram presented in *Figure 1*. All around, assuming a place of any unknown nodes was found, then the anchor nodes, at that point, exist insignificantly overlooked. Thus, reducing the node number impacts the node situation.

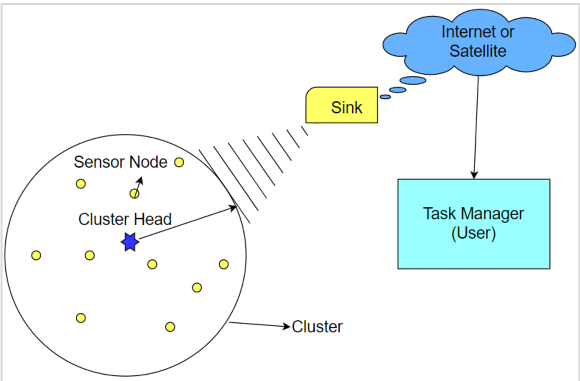

Figure 1 Basic WSN

1.1Background

Continuous targets in WSNs are addressed using a multi-mobile service node scheduling strategy and a convolution-based localization method. The simulation experiment demonstrates the method's and approach's capacity to successfully handle the (i) Matrix deflation in WSNs and can be managed via convolution. (ii) Some information is lost during convolution, although the amount depends on the cryptographic key management size. In our 2nd segment investigation, several met heuristic computations were used in WSN limitation. The outcomes of those investigations focus on showing that these computations have adequately and most certainly restricted limits in mistakes. The sensor nodes are forced to position themselves without the help of any specialized gear like a global positioning system (GPS) or manual configuration. Sensor node connects without infrastructure using a wireless, lossy channel, increasing the performance of the node location accuracy and network lifetime, and reducing the localization error is difficult [10]. The bunch place mechanism groups with additional bunch communities. They are, for the most part, most of the base station. WSNs are classified as keen on a few states and separate, ordinary, group focus, and passage. At last, disconnected nodes save a protected nearby nodes table where nearby node data will be put away. Determination of the come-together direction is viewed as exceptionally fundamental in the grouping. Bunching in sensor networks is generally power-productive. In a more extensive term, restriction strategies are arranged into without-range and reach-based techniques [11]. Range-based confinement takes advantage of the distance interfacing with all types of nodes' availability of information. Then again, range-based strategies are fine-grained confinement techniques, while coarse-grained, without-range techniques are used [12]. The place of a restricted obscure node is significant because it tackles greater WSN issues like directing and data aggregation. Therefore, it is important to zero in on confinement techniques in WSN works [13]. There are two different possible conditions for dispersing, also a concentrated limitation. In previous years' papers, everyone tracks down to obscure the node without anyone else, even if it is the last choice. Every hub data is communicated to a brought-together part for additional handling to get data about the position. Moreover, the grouping system of the nodes in the subsequent one is separated for an interconnecting organization is represented by the name of bunches, forming the group with all the nodes, and the group head is going to coordinating with all the nodes in that group it is called cluster formation and the group head called cluster head [14].

1.2Challenges

The sensor nodes are forced to position themselves without the help of any specialized gear like a GPS or manual configuration. The sensor nodes empowered with aggressive circumstances should remain energetic for an extended period. Changing the batteries is very difficult [15], the sensor node connects without infrastructure using a wireless, lossy channel, increasing the performance of the node location accuracy and network lifetime, and reducing the localization error is difficult [16]. Even though WSNs have changed in many ways, they are still networks with limited energy, computing, memory, and communication resources [17]. Recently, a new methodology was utilized where WSN restriction depends on streamlining issues on the complex with multiple models that will be feasible by using another technique called stochastics techniques which are based on population.

1.3Motivation

This challenge concentrates on increasing the node location accuracy and network lifetime performance and reducing the localization error. Due to the need for minimal device complexity and low energy consumption to extend the network's lifespan. Stick good maintenance between data and the signals transmitting process capabilities is necessary. How to increase network longevity, reduce localization error, and improve node location accuracy. The application for data-driven monitoring and reporting, as well as the creation of efficient algorithms and protocols in terms of computing and energy, have been the focus of research on WSN. This drives significant research efforts, standardization efforts, and commercial expenditures in this area.

1.4Objective

The protocols must be created from the outset for effective energy resource management. The main objective proposed enhance network lifetime, node location accuracy, and localization error reduction performance. The proposed GA for efficient clustering, and increasing accuracy and efficiency Modified GA is derived from the basic GA the basic GA followed by the organic behaviors implemented into the optimization area. This approach is an ordinary collection. The solution for the fixed dimension of binary numbers is decoding and encoding chromosomes. The intervals are zeros and ones through N-numbers of bits.

The following sections provide an overview of the various components that make up this work.: section 2 explores into prior research endeavors concerning Localization is discussed in the following section. In section 3, a brief overview of the utilized and proposed GA is presented, and the Method for building sensor node clustering and localization in a scenario focused on WSN localization. Moving on to section 4, there is a detailed explanation of the proposed fitness function. Encompassing power efficiency, distance estimation, and coverage association definitions, and outlines the performance evaluation of the GA. Ultimately, section 5 encapsulates the research summary and the resultant conclusions.

2.Literature review

Coverage area-based strategies are arranged in 4 significant lessons, to be specific, dissimilarity time influx (DTI), arrival time (AT), arrival of angle, and RSS. They propose an innovative approach called genetic-based distance vector hop (DV-HoP) localization. By incorporating GAs into the DV-Hop technique, we aim to enhance the accuracy of node localization further. This hybrid approach promises to provide more precise and reliable localization results than traditional DV-Hop techniques [18]. The proposed scheme utilizes GAs in the sampling process to further enhance efficiency. This approach significantly improves the accuracy of the localization process by efficiently exploring and narrowing down the possible locations of the target node [19]. Bunching nodes are keen on setting monitor energy levels and limiting questions next to the organization from the time nodes send the monitored data to the heads of the group by decreased length. These functions follow them with grants territory of transmission [20]. A portion of the current connected examination study is shortly considered. Proposed the Creators a productive crossover bio-stirred optimization in limitation techniques applied in modern WSNs [21]. The focus was on establishing a secure channel for data transfer between nodes in a network using quantum key distribution (QKD). QKD is a quantum cryptographic technique that enables secure communication by distributing cryptographic keys between communicating parties, utilizing the principles of quantum mechanics to ensure the keys' confidentiality [22]. Specified the present confinement plus checking arrangements, sensors node limitation, and target following innovation for WSN must be inspected according to their viewpoints the precision, expanding normal existence regarding coordination hypothesis, molecule channel, sans range hypothesis, and diverse figuring draws near [23]. An anchor node optimization approach with minimum standard deviation and minimal error propagation has been developed by examining the range-based positioning algorithm's error propagation. An innovative soft computing method called Adaptive plant propagation to find these movable nodes' optimal positions algorithm is presented [24]. They benefited and utilized the cluster-based algorithms, which include and distinguish nodes available in a bunch through revealing the occasion toward group place (likewise group head) node as per a question, passing on all perceptible data will be sent into the receiving ending [25]. By combining efficient node clustering and distributed multi-hop routing, aims to improve several aspects of WSN such as network lifetime, energy efficiency, and load balance. The research aims to achieve better control over the states of nodes in a network, particularly focusing on handling congestion situations. The congested nodes can make optimal routing decisions by using link permutations, transition probabilities, and immediate rewards. The time episode of isolation allows nodes to recover from congestion, and the simulations using network simulation 2 demonstrate improved data forwarding in scenarios involving overloaded and isolated nodes. Overall, this work enhances the reliability and efficiency of data transmission in congested network environments. To present our findings effectively, we have developed a graphical model that visually represents the algorithm's performance metrics, such as accuracy and efficiency. The algorithm introduces a distinctive approach by formulating fitness parameters that combine various crucial factors to determine cluster heads effectively [26]. The novel and adaptive routing protocol combines energy awareness, trust-based mechanisms, and GAs to improve WSN security and energy efficiency. By resisting attacks, optimizing energy consumption, and outperforming existing secure routing protocols, demonstrates its potential as a promising solution for various WSN applications [27]. A proposed event-driven energy-efficient protocol employs a GA in a heterogeneous WSN. The protocol leverages fitness function values derived from parameters such as the node's remaining energy, minimum distance to the base station, and neighborhood degree. The evaluation criteria encompass network stability, energy consumption, first node death, and the number of living nodes per round [28]. The developed algorithms effectively tackle the coverage problem in diverse environments [29]. This paper proposes a multi-energy supply system for intelligent control of agricultural greenhouses, using an adaptive improved GA. Experimental results demonstrate precise control with temperature deviation < 0.5°C, humidity deviation < 1% RH, and stable carbon dioxide concentration with fluctuations < 2.5% [30]. The paper introduces a novel method that utilizes a GA to improve network coverage by reducing random sensor node deployment. The method employs an enhanced two-point crossover technique to ensure node connectivity and variable-length encoding. Through simulations, the results showcase the superiority of this approach, achieving higher coverage rates (9.69%) and lower overlapping ratios (35.43%). Additionally, the method successfully reduces the overlapped node area (65.80%) and network cost (13%) effectively [31]. This approach enhances the network's lifetime and addresses energy conservation challenges, contributing to sensor networks' more efficient and sustainable operation in various applications [32]. The proposed algorithm is an energy-efficient data aggregation mechanism (EEDAM) that utilizes blockchain for security. It employs cluster-level data aggregation to save network energy and incorporates edge computing for reliable and fast IoT services. Blockchain integrated into the cloud server validates edge computing, ensuring secure services for IoT devices [33]. The simulation results provide empirical evidence of the algorithm's effectiveness in improving accuracy performance and reducing energy consumption, making it a valuable contribution to WSN research [34]. The proposed sleeping node scheduling methodology aims to optimize energy consumption in WSNs by strategically scheduling nodes into active and sleep modes. Clustering formation balances the energy load, fuzzy similarity theory categorizes nodes based on relevant criteria, and redundant node sleep scheduling further enhances energy efficiency [35]. The clustering algorithm offers notable advantages over the direct transmission approach without clustering, including better network performance, prolonged network coverage, and improved access to the latest information from diverse locations. These findings highlight the importance of implementing clustering techniques to enhance the overall efficiency and reliability of the network [36]. By introducing a novel multi-objective cost function, this approach significantly extends network lifetime, balances interference, and improves throughput compared to existing methods, showcasing its potential as a promising solution for optimizing wireless networks [37]. The proposed GA-based joint clustering and routing protocol significantly advances energy-efficient WSN management. By integrating GA to optimize Clustering and routing decisions jointly, the protocol achieves notable improvements in first-node dead statistics, leading to greater network stability and a prolonged lifetime. These findings underscore the protocol's potential to enhance energy efficiency and performance in WSNs [38]. This study aims to prolong the network lifetime by solving the non performing(NP)-hard problem of maximum coverage set scheduling, which is proposed and outperformed a recently proposed approach in achieving near-optimal solutions for scheduling coverage sets [39]. This study examines the subject of interest, the location error in a fingerprint-based indoor localization system that uses hybrid fingerprints. Hybrid fingerprints combine different types of location data for more accurate positioning. The paper presents a machine learning-based hybrid fingerprint localization algorithm to improve indoor localization accuracy further [40]. The localization algorithms are a fusion of bounding-box and kalman-filter methods, enhancing accuracy across various field types. This algorithm employs hop-based techniques and has shown remarkable localization precision in diverse 3-dimensional fields with distinct shapes, surpassing recently published approaches. For future work, we plan to deploy this algorithm on real WSNs to address localization challenges in practical scenarios

[41]. A few variables to consider in dragging out the life of organizations is using the increases of compromises like power, dormancy, and precision, combined with utilizing various layered structures [42]. The proposed work presents an end-to-end deep learning model incorporating a key point-regression mode. Experimental results indicate that this method outperforms existing mainstream models in several aspects. It achieves superior localization accuracy (97.01%), faster inference speed (125 frames per second), and greater robustness on the same platform [36]. The proposed classification methodology is based on support vector machines and is designed to handle dynamic environmental conditions and obstacles. It leverages the derived cross-correlation peaks acquired through waveform and channel analysis, offering enhanced robustness features [43]. The form of tabu search-optimized PSO is a range-based localization approach that utilizes optimization techniques for sensor localization estimation. It enhances the PSO algorithm by incorporating tabu search to find the best local neighbor and includes limit and performance checks during particle evolution. Compared to other methods it significantly improves localization accuracy. The results demonstrate an efficient optimization algorithm for indoor localization problems in WSN, with rapid convergence toward optimal solutions [44]. In this method, a multi-objective variant of the multi-objective gorilla troops optimizer algorithm uses external archive and PSO dominance in silverback picking. Simulations on (1000-10,000 nodes) show that outperform other multi-objective models with improved fitness functions and reduced energy consumption [45]. Then again, range confinement techniques incorporate the meddle algorithm, monte carlo localization, estimated position in triangle test (EPTT), neighboring tip-base technique, supposition-base organize method, and shapeless technique. this requires creating novel force-proficient options in contrast to a portion of the current conventional remote systems administration challenges, which incorporate the middle right of entry organize, personality association, data transmission circulation, directing, and safety. Confinement happens once while thinking about static nodes, though following is a constant limitation of the cell node over the long run. Bunching is a favored strategy for accomplishing able and available in general execution implemented in WSN.

2.1Reason for selecting genetic algorithms(GA)

GA is a popular choice for optimizing WSNs (WSNs) for several reasons: WSN optimization problems often involve a large and complex search space. GAs is well-suited to exploring this space efficiently by maintaining a population of potential solutions and iteratively evolving them across generations. This allows GAs to discover near-optimal or optimal solutions even in high-dimensional search spaces. Many WSN optimization problems exhibit nonlinearity and nonconvexity, making them difficult to solve using traditional optimization techniques. GAs can handle these problems because they are not based on gradients or mathematical models. GAs has the potential to find global optima instead of getting stuck in local optima, which is a common problem in optimization problems for WSNs. Their stochastic nature allows them to explore different areas of the solution space. GAs can be tailored to various WSN optimization objectives, including energy efficiency, coverage, connectivity, localization accuracy, and data routing. By defining appropriate fitness functions, GAs can optimize WSNs for application-specific requirements. GAs are inherently parallel algorithms that can be implemented on distributed WSNs or in parallel computing environments. This property can lead to faster convergence and more efficient optimization.

2.2Justifying the reason for selecting GA

GAs are often chosen for optimizing WSNs (WSNs) for several compelling reasons: Complex search space: WSN optimization problems often involve a huge and complex search space with numerous variables, constraints, and objectives. GAs excel at exploring such complex spaces, cultivating a population of potential solutions, and evolving them across generations. This parallelism enables GAs to efficiently navigate a broad solution landscape. Nonlinear and nonconvex nature: Many WSN optimization problems have nonlinear and nonconvex characteristics, making them difficult to solve using traditional mathematical optimization techniques. As stochastic search algorithms, GAs do not rely on the smoothness or convexity of the objective function and can effectively handle these complexities. Global optimization: GAs are good for finding global optima rather than being trapped in local optima. They can explore different areas of the solution space, which is crucial in WSNs where suboptimal solutions can lead to network inefficiencies or failures.

Flexibility and customization: GAs provide flexibility in defining fitness functions tailored to specific WSN goals. Whether the goal is to maximize energy efficiency, coverage, connectivity, or lifetime, GAs can be tailored by appropriately defining the fitness function, making them highly customizable for different applications. Multi-Objective Optimization: Many WSN options.

2.3Final review analysis

These challenges include energy constraints, limited processing, and memory capabilities, communication range and reliability issues, scalability concerns, network topology changes, data aggregation and fusion complexities, security and privacy vulnerabilities, time synchronization difficulties, localization challenges, varying quality of service (QoS) requirements, and the deployment and maintenance obstacles. Overcoming these challenges requires continuous research and innovation from experts in various fields, including wireless communication, networking, distributed systems, signal processing, data analytics, and energy management. As technology advances, addressing these challenges becomes crucial to unlocking the full potential of WSNs in diverse applications, by developing efficient algorithms, protocols, and security measures, we can harness the power of WSNs to create more intelligent and interconnected systems that benefit society in numerous ways.

2.4Study limitation for WSNs

WSNs are an active area of research and deployment, and like any other field, they come with their limitations and challenges. These limitations can impact the design, deployment, and performance of WSNs. Here are some common limitations associated with WSN's Limited power resources: Most WSN sensors are battery-powered, meaning they have limited power resources. This limitation can significantly impact network lifespan. Energy-efficient protocols and algorithms are crucial to mitigate this limitation. Limited processing power: Sensor nodes typically have limited processing capabilities. This limitation affects the complexity of the algorithms that can be implemented on these nodes and may require lightweight and efficient algorithms. Limited memory: Sensor nodes often have limited memory, limiting the data they can store and process [46]. This limitation can impact data aggregation and storage strategies. Limited communication range: The communication range of sensor nodes is typically limited, leading to connectivity issues and the need for multi-hop routing.

3.Methods

The proposed approach hinges on effective clustering and robust global search using GA to enhance accuracy and efficiency. GA is applied in networking to address complex, multi-dimensional optimization problems where traditional methods might struggle. They provide a flexible, heuristic-based approach to finding solutions that can adapt to dynamic environments, handle multiple objectives, and consider a wide range of constraints, making them valuable tools in the design, optimization, and management of various types of networks. The decision-making technique for everyone is based on the capacity of the fitness of the chromosomes technique to control the mating process. The function of the chromosome is to hold the results by its shape and select the accordance with the selection method chromosomes are selected past one which of the following is a higher possibility of having a good fitness. After selecting based on the fitness of the chromosomes based on their ranking for value.

3.1Crossover

The crossover operator combined the pairing of two selected chromosomes, making offspring that will share the positive characteristics of both parents. *Figure 2* shows the model configuration genetic material for the entire chromosome, selecting two arbitrary points, C1 and C2-the results of the swap with a nearby one.

1	0	1	1	0	0	1	1	0	0

Figure 2 Depicts an example structure of a chromosome

3.2Selection of decision-making technique

To manage the mating process for everyone, the decision-making technique depends on the fitness capacities of the chromosomes. The higher the fitness value of these chromosomes, the more likely they will be chosen. More fit solutions have a better probability of replicating. Conversely, ranking occurs after the genetic material using the maximum strength worth has been assigned to the most suitable genetic material. The function depicts how close an answer knows how to alter toward achieving the optimum consequences. One or more individuals multiply to produce children based on probability collection's charge, e. The (Probe) represents the selection probability of each which is shown in Equation 1.

$$the\ (Prob)^{n} \frac{Fn^{\mathrm{n}}}{\sum_{b=1}^{Np} Fn^{m\prime}} \qquad (1)$$

Where n ∈ {1, . . ., Np}, the strength is chosen to be nth, and Fnn can represent it, and the choice of genetic material labeled by n and its dependent to r ∈ (0, 1) chance integers. Definition of collective likelihood CP^n as shown in Equation 2, which satisfies the genetic material chosen at opportunity within $CPni - 1 < r \leq CPn$. The Localization area of the RSS (wo) is a dependable location inside, as shown in Equation 3.

$$CP^n = \sum_{m=1}^{Np} Fn^m \quad (2)$$

$$the\ RSS(wo) = p_{tr} + k_{en} - 10\eta \log\left(\frac{w_0}{Edw_1}\right) + \alpha + \beta \quad (3)$$

Where Ptr denotes the nominal transmission power (dBm), Ken is the system constant, denotes the route loss coefficient, w1 denotes the far-field suggestion space of the transmitter, denotes rapid departure result, and denotes chance reduction caused as a result of surveillance. By altering w0, the actual transmitter-receiver distance, the RSS is examined. Before the localization procedure, the anchor nodes' specific locations are recognizable. The proposed GA's flowchart is illustrated in *Figure 3.*

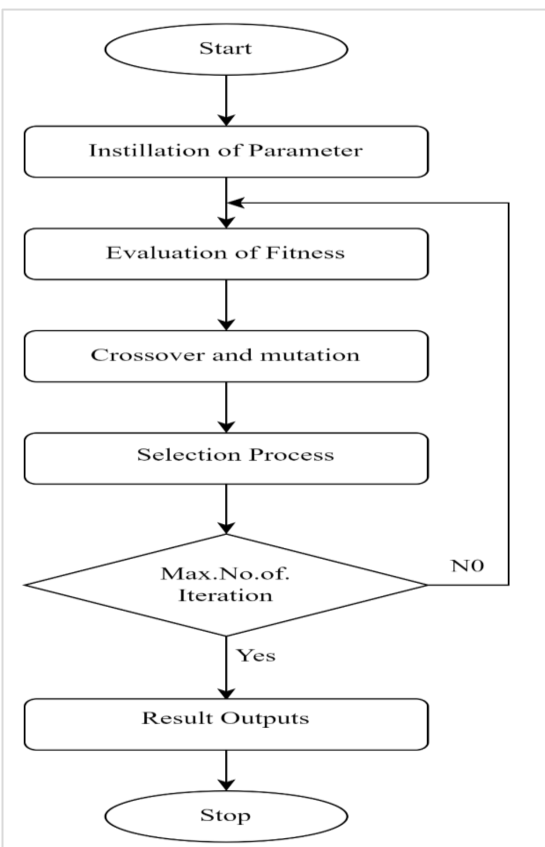

Figure 3 Flow Chart of GA

Known nodes are another term for this. "A" stands for anchor node counts. LN denotes the collection of all the sensor nodes within the range of the network. Lx represents a recognized node location (RLx, SLx)—also, unidentified nodes whose positions.

Are determined by a specific localization algorithm. LN is used to denote a group of unidentified WSN nodes, are shown in Equations 4, 4.1 and 4,2.

$$L_N = L_x | x = 1,2, \dots \dots A \quad (4)$$

$$H_N = H_x | x = 1,2, \dots \dots \dots B - A \quad (4.1)$$

$$R_N = E_x | x = 1,2, \dots \dots \dots C \quad (4.2)$$

The Hx distinct by (Rhx andShx) is undetectable in real-time requests. Assume that the communication range has a radius of R. Given that Ra and Rb represent two activated sensor nodes, Ra is considered a direct neighbor of Rb if Ra is positioned inside Rb's broadcasting range. Please assume that the unknown node Hx contains m nearby suggestion nodes $y = 1, 2 \dots, m$ and the e1, $e2 \dots \dots, em$. to get (R0hx, S0hx), we can use the Euclidean distance formula as shown in Equation 5.

$$the\ Ed_{xy}^1 = \sqrt{(R - R_{ey})^2 + (S - S_{ey})^2} \quad (5)$$

Where (r, s) is an unresolved dimension, and Rey, Sey is Ey's location. It is impossible to identify the actual junction (area) Ey on wide due to distance measurement error z and the predicted position (R0Lx, S0Lx). The estimated distance Ede0xy at that point is calculated using the estimated function shown in Equation 6 (R0Lx, S0Lx).

$$the\ Ed_{xy}^0 = \sqrt{(R_{LX}^0 - R_{ey})^2 + (R_{wc}^0 - R_{ey})^2} \quad (6)$$

The purpose of placement is to obtain a tiny distance from Ed1xy to Ed0xy; due to the improbability of Edxy, the actual space is dissimilar. Finally, we define that location issue Hx as shown in Equation 7 and the expanded equation as shown in Equation 8.

$$H_x = \sum_{y=1}^{n} wy \left(Ed_{xy}^0 - Ed_{xy}^1\right)^2 \quad (7)$$

$$H_x = \sum_{y=1}^{n} wy \ \left(\sqrt{\left(R - R_{ey}\right)^2 + \left(S - S_{ey}\right)^2} - Ed_{xy}^1\right)^2 \quad (8)$$

Where $w_y = (\frac{1}{Ed_{xy}^1}) \sum_{x=1}^{m} (\frac{1}{Ed_{xy}^1})$he provides a better grasp of the reference point closer to Hx, Ed; however, if Ed >= Edo. As a result, the radio signal taken to send an h-bit communication across the space Ed expressed as Equations 9,10,11,12 and 13.

$$LE_x = \frac{1}{R}\sqrt{(P_{ux}^0 - p_{ey})^2 + (q_{wc}^0 - qey)^2} \quad (9)$$

$$the\ \mathrm{Ed}_0 = \sqrt{\varepsilon_{fs}/\varepsilon_{mp}} \cdot \varepsilon_{fs} \quad (10)$$

$$w_y = \left(\frac{1}{\mathrm{Ed}_{xy}^1}\right) \sum_{x=1}^{m} \left(\frac{1}{\mathrm{Ed}_{xy}^1}\right) \quad (11)$$

$$E_T(h) = h \times E_{elec} \quad (12)$$

$$E_i = E - E_1 \quad (13)$$

This should be done systematically so that each node in a vast network wastes as little energy as possible, as shown in Equations 14,15,16,17, and 18.

$$D_G^0 = \sum_{p_a \sum N}^{N} dist(p_a, q_b) \quad (14)$$

$$D_G^1 = \sum_{q_b \sum N}^{N} dist(p_a, q_c) + dist(p_c, q_b) \quad (15)$$

$$D_i = \sum_{p_y \sum N} dist(p_x, q_y) \quad (16)$$

$$CL = \begin{cases} 1, if \|p_x - p_y\| < S_r \\ 0,\ Otherwise \end{cases} \quad (17)$$

$$C_i = \bigcup_{y=1}^{N} \sum C_y \frac{C_y}{C} \quad (18)$$

The overall fitness value, which must be estimated while reducing, represents the previous fitness minor targets shown in Equations 19 and 20.

$$F_i = w_1 E_i + w_2 D_i + w_3 C_i \quad (19)$$

$$\sum_{i=1}^{3} w_i \geq 0, w_i \in (0,1) \quad (20)$$

3.3The proposed genetic algorithms (GA)

Step 1: Define the problem parameters
num_nodes = 50
max_x, max_y = 100, 100
population_size = 100
generations = 100
mutation_rate = 0.1
Step 2: Define the fitness function
def fitness function(chromosome):
Step 3: Initialize the population with random solutions
Step 4: Perform single-point crossover between two parent chromosomes
def crossover (parent1, parent2):
Step 5: Apply mutation to the chromosome.
def mutate(chromosome):
for i in range(num_nodes):
if random. Random () < mutation_rate:
chromosome[i]= (random. randint (0, max_x), random. randint (0, max_y))
return chromosome
Step 6: Select parents for crossover using tournament selection
Step 7:Main GA function
def GA ():
population = initialize population ()
for generation in range(generations):
Step 8: Evaluate fitness
fitness scores = evaluate fitness(population)
Step 9: Select parents for crossover
parents = tournament selection (population, population_size)
Step 10: Perform crossover and mutation
next generation = crossover_and_mutate(parents)
Step 11: Replace current population with next generation
population = next_geneation
Step 12: Identify the best solution
best solution = max (population, key=fitness function)
return best solution.

4.Results and discussion

The proposed methodology GA uses the simulation environment. GAs are metaheuristics inspired by evolutionary algorithms and natural selection. They are particularly suited for addressing optimization problems in WSNs. GA is an optimization technique inspired by biological behaviors. Each candidate is represented by chromosomes with a fixed dimension of binary numbers containing 0s and 1s, using decoding and encoding methods. The GA procedure encompasses initialization, selection, crossover, and mutation. The GAs have been widely used in research to optimize various aspects of WSNs, including energy-efficient routing, data aggregation, node scheduling, and topology control. They offer a powerful and versatile approach to improving the performance and longevity of WSNs in practical applications.

4.1The software description

Spyder is an open-source integrated development environment (IDE) tailored specifically for scientific computing and data analysis in Python. It provides a comprehensive development environment with advanced editing, debugging, and profiling tools, making it suitable for scientific and numerical programming tasks. Key features of Spyder include Interactive Console: Spyder offers an interactive Python console, which allows you to execute code and view results in real time. This feature is handy for data exploration and experimentation. Code Editor: The IDE includes a powerful code editor with syntax highlighting, code completion, and advanced editing capabilities. It supports features like code folding, automatic indentation, and integrated documentation. Variable Explorer: Spyder provides a variable explorer that allows you to inspect and modify variables in memory. It provides a convenient way to track and explore data during development. You can set breakpoints, step through the code, and inspect variables to understand how your program is executing. The simulation parameters as shown in *Table 1*. Profiler: Spyder integrates a profiler that helps you identify performance bottlenecks in your code. It provides detailed information about the execution time and memory usage of different parts of your program. Plots and graphical user interfaces (GUI) integration: spyder has integration with popular python libraries such as matplotlib and pyot, allowing you to create and interact with actions and develop GUI quickly. Plugin system: spyder supports a plugin system that will enable you to extend its functionality and customize it will suit your needs.

Table 1 Simulation components

Components	Range of components
Number of Nodes	300
Coverage area	500×500 m^2
Packet size	200 bits
Initial Energy	2J
Distance(do)	87m
Transmission Power (ET.)	50nJ/bit
Receiver energy (ER.)	50nJ/bit
Cluster Heads	5
Generation	100
Population size	100
Selection	0.2
Crossover	0.8
Mutation rate	0.01
Anchor node	50-175
Iterations	50

4.2Installing WSN nodes

Figure 4 depicts installing WSN nodes in the area for coverage. There are various community-developed plugins available for additional features and integrations. The proposed strategy fundamentally worked on the network's existence contrasted with other methods. It is expanding the nodes of essential by a maximum of 200 iterations. The organization channel after a few cycles when sensor nodes are empowered. When the quantity of emphases comes to 180, contrasted with ACGL's 50 dynamic nodes, GA has 60 active nodes. Simultaneously, DV-HOP, centroid localization algorithm (CENTA), enhanced distance vector hop (EDV-HOP), and Clustering In genetic algorithm localization (CGAL) have somewhere between the fourth and twenty-five involved nodes. Under the created energy-productive grouping restriction approach dependent on the hereditary algorithm, GA showed a preferred result over the DV-HOP as a short form of distance vector-hop.

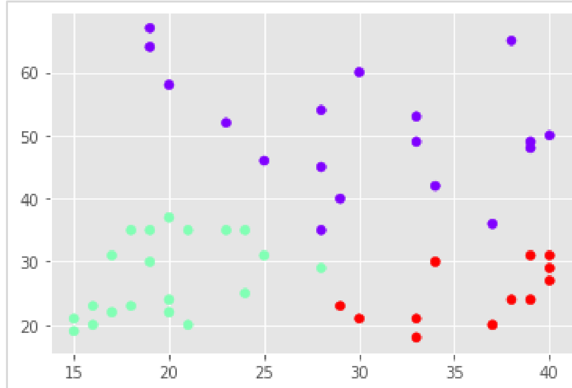

Figure 4 WSN nodes

4.3Cluster formation of the sensor Network

Figure 5 shows the cluster formation of the sensor node in the network by contrasting the inclusion against the network node connection; looking from 10 to 70, the influence of linked nodes is concentrated. In our examination, 200 invigorated sensors possess 200 by 200m2 arrangement regions. With an increment in associated nodes, the limitation inclusion for DV-HoP, CENTA, EDV-HOP, and CGAL, and an increment when the readings on the even hub arrive at 50 associated corners, the organization inclusion increments for GA at the point when the inclusion area marker collects, the strength of the node-to-node link grows after 70 bars.

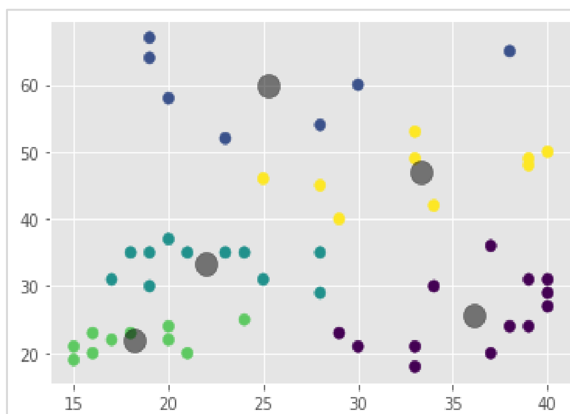

Figure 5 Cluster formation

Figure 6 shows the GA clustering formation the thickness of adjoining invigorated sensors warrants practical and very much constructed association among known and obscure node points. By and large, our advanced situating technique is better than other existing strategies regarding exactness.

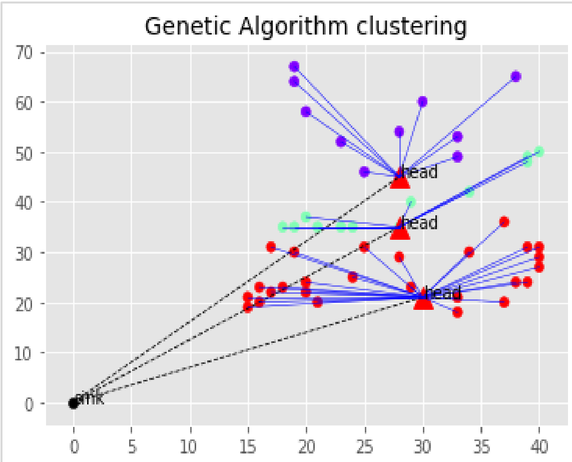

Figure 6 GA clustering

Figure 7 shows the K-means clustering formation. GA performs superior in the combinations time compared to other algorithms. The GA successfully transfers around 90% of data to its last objective. With an expansion in the repetition quantity.

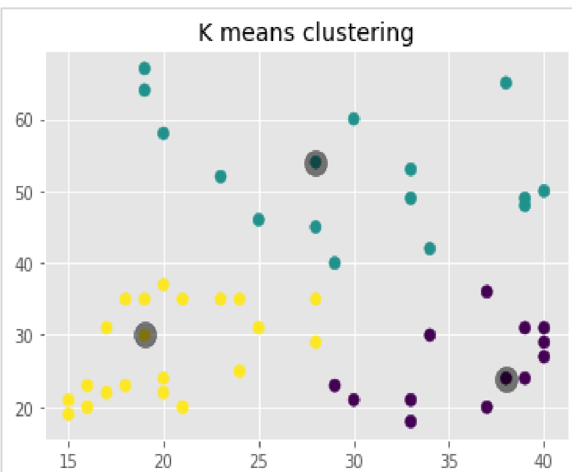

Figure 7 K-means clustering

4.4Energy consumption

The capacity of genetic material to handle other scenarios contributes to lowering used energy and extending the network system's lifespan. *Figure 8* shows the reduction in power with respective K-value. The channel description still used the total distance between the receiver and the transmitter. Acknowledge of h-bits communication sent. The radio must likewise spend energy (10). Modulation, filtering, digital coding, and integrating signal dispersion all impact E_{elec}. Still, the amount of energy required to magnify the system is not, as _(fs) Ed (2) or _(fs) Ed (3) show (4).

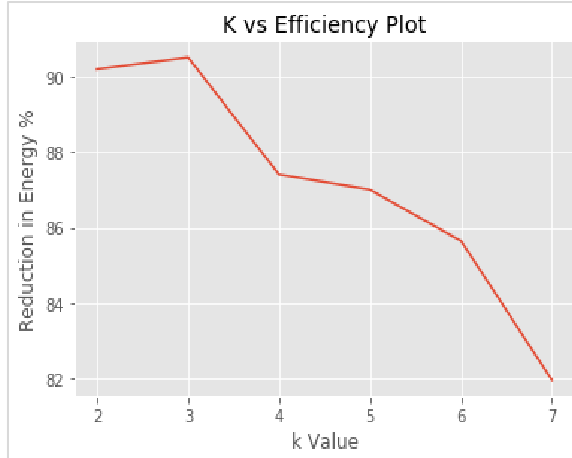

Figure 8 Reduction energy Vs. K-Value

The reception structure is employed depending on the traveling distance and error suitable as per the bit. E_{elec} is the term used to describe the electronic energy required by an electronic circuit. *Figure 8* shows the reduction in energy with respective K values. *Figure 9* shows the energy reduction with the individual number of iterations.

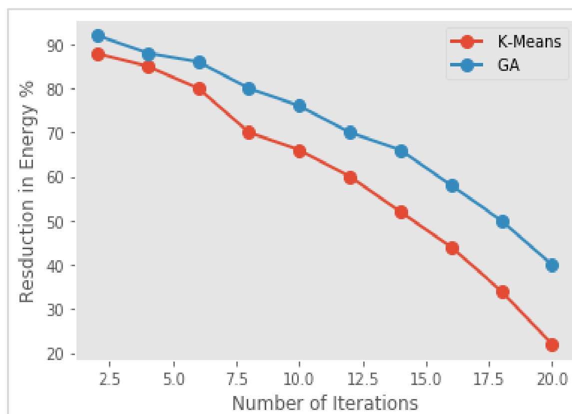

Figure 9 Reduction Energy Vs. iterations

4.5The comparison involves the concepts of threshold, average localization error (ALE) analysis, and the impact of anchor ratios in object detection models

The anchor ratios can significantly impact the performance of the object detection algorithm. If the anchor ratios are not appropriately chosen, objects might be harder to detect or more prone to localization errors. Finding the optimal anchor ratios often involves experimentation and tuning to achieve the best balance between coverage of object shapes and computational efficiency. Analysis is a performance metric used to evaluate the accuracy of object localization algorithms. It is commonly employed in computer vision tasks like object detection and localization. ALE measures the average distance between the predicted bounding box (or localization) and the ground truth bounding box for a set of objects in an image dataset. Thresholding: Thresholding is a common technique in various applications. It involves setting a threshold value to convert a grayscale or continuous signal into a binary image or a discrete form. The threshold value acts as a decision boundary, where pixel values above the threshold are assigned to one class, and values below the threshold are set to another.

4.5.1Performance analysis

During the evaluation and analysis, the assessment considered both localization accuracy and cost metrics. A contrast was drawn between the outcomes produced by the suggested approach and those originating from DV-Hop, weighted centroid localization (WCL), improved DV-MaxHop, and enhanced DV-Hop. The performance analysis was guided by the subsequent metrics.

4.5.2Accuracy metric

A WSN setting is considered, involving the deployment of 100 anchor nodes. This assists in establishing the suitable value for "t." As the parameter "t" converges towards six, the evaluation of the accuracy metric is carried out within the context of the following considerations. Analysis of average localization error, investigation into the impact of anchor ratios, and evaluation of node density variation consequences.

4.5.3Analysis of average localization error

As a result, the ALE serves as a metric for gauging the accuracy level achieved by the implemented algorithm. Equation 21 is employed to compute the ALE, which subsequently serves as the criterion for evaluation.

$$ALE = \frac{\sum_{i=1}^{Sn}\sqrt{(a_i-a)^2+(b_i-b)^2)}}{n*r} \quad (21)$$

In Equation 21, the numerator captures the Euclidean distance encompassing both the projected (a, b) and factual positions (ai, bi) of the unidentified node, alongside the computed error distance. Here, "Sn" denotes the overall count of nodes, and "r" signifies the radius. The algorithm introduced in this research serves to augment localization accuracy by mitigating localization errors. This enhancement is illustrated in *Table 2,* where improvements are observed across maximum, minimum, average, and standard deviation measures [46].

Across the metrics of minimum, maximum, and average, the proposed method demonstrated enhanced performance compared to the other three localization algorithms in terms of the average localization error.

Table 2 Average localization error

Range	DV-Hop	Weighted clustering	DV-HoP (Max)	DV-Hop (Normal)	DV-Hop (HCE)	Proposed GA
Maximum	1.8	1.44	-	0.40	0.299	0.25
Average	1.5	1.4	0.51	0.29	0.21	0.25
Minimum	1.4	1.32	-	0.29	0.19	0.1
Standard deviation	0.13	0.03	-	0.02	0.0029	0.0002

4.5.4Influence of anchor ratios

The anchor ratio represents the proportion of anchor nodes engaged in the localization process. While maintaining the total node count and communication radius at 500 and 100 meters respectively, elevating the anchor ratio results in a decrease in localization error. *Table 3* presents an empirical assessment of average localization error across varying anchor node ratios. This achievement results in reductions of error by 79.41%, 78.11%, 11.26%, and 5.5%, respectively. With an escalation in the count of network anchors, there is an observable enhancement in localization accuracy. However, it is worth noting that pre-establishing anchor positions using GPS can entail substantial costs and energy consumption.

4.5.5Impact of threshold

These outcomes of the impact of the threshold are presented comprehensively in *Table 4*.

Table 3 Provides a comparison of localization errors across different influences of anchor ratios

Number of Anchor	DV-Hop (Normal) [46]	Weighted clustering [46]	DV-Hop (Max) [46]	DV-Hop (Developed) [46]	DV-Hop (HCE) [46]	GA (Proposed)
50	1.8	1.36	0.70	0.3528	0.29495	0.274
75	1.62	1.34	0.61	0.3526	0.2946	0.251
100	1.61	1.35	0.48	0.3464	0.2985	0.232
125	1.56	1.332	0.39	0.3013	0.3000	0.200

Number of Anchor	DV-Hop (Normal) [46]	Weighted clustering [46]	DV-Hop (Max) [46]	DV-Hop (Developed) [46]	DV-Hop (HCE) [46]	GA (Proposed)
150	1.49	1.337	0.34	0.3088	0.2946	0.198
175	1.4	1.32	0.32	0.3066	0.2897	0.164

Table 4 illustrates a contrast in the energy consumption of the proposed algorithm under varying threshold values with a fixed number of anchor nodes set at 150

Threshold	DV-Hop [46]	WCL [46]	Improved DV-Hop [46]	DV-Hop (HCE) [46]	Proposed algorithm
3	250,850	217,676	176,760	180,000	190,000
5	250,850	217,676	178,070	180,210	190,210
6	250,850	217,676	179,460	180,900	190,900

4.6Localization error

The total distance travelled begins with an electrified node point and ends with a different sensor position, the theoretical length of 2 nodes. It is written as distance Pa and qb. On the other hand, to come closer to our aim, the Cluster and location node space should be minimal compared to the remoteness between the Cluster and the sensor nodes on another side. Dist. (pa, qc) denotes the latter, while dist. (Pa, QC) represents the former (Pc, qb). *Figure 10* illustrates the relationship between the localization error (m) of the proposed method and the number of clusters in the DV-Hop algorithm. *Figure 11* shows this relationship for the CENTA algorithm, while *Figure 12* presents it for the EDV-Hop algorithm. *Figure 13* demonstrates the same for the CGAL algorithm, and *Figure 14* for the energy-efficient clustering and localization method based on a genetic algorithm (ECGAL). Finally, Figure 15 compares the proposed method's localization error with the number of clusters against alternative approaches, as referenced in [22].

4.7Alive node in the network

Every WSN can be compared to an undirected link, and so on. E is for the edge set $e = e1, e2, \ldots, ef$, a finite actual number, denoted by the symbol Wi, is also present at each network edge. *Figure 16* shows the number of Alive Node Vs. Number of Iteration for DV-Hop algorithm, *Figure 17* shows the number of Alive Node Vs. Number of Iteration for CENTA algorithm, *Figure 18* shows the number of Alive Node Vs. Number of Iteration for EDV-Hop algorithm, *Figure 19* shows the number of Alive Node Vs. Number of Iteration for CGAL algorithm, *Figure 20* shows the number of Alive Node Vs. Number of Iteration for ECGAL algorithm, *Figure 21* depicts the correlation between the count of operational nodes using the proposed method, the number of iterations, and a comparative analysis against alternative approaches [22].

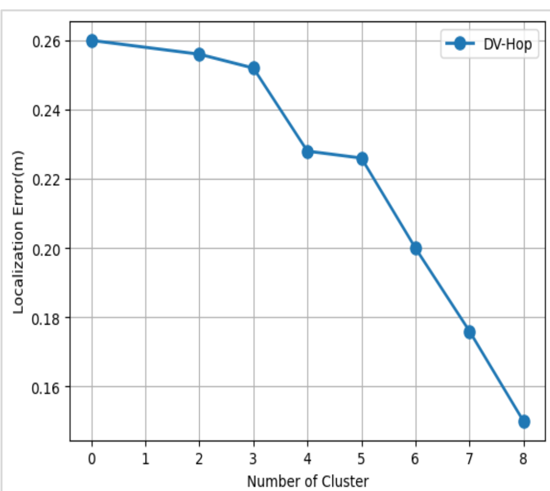

Figure 10 Localization Error(m) for DV-Hop

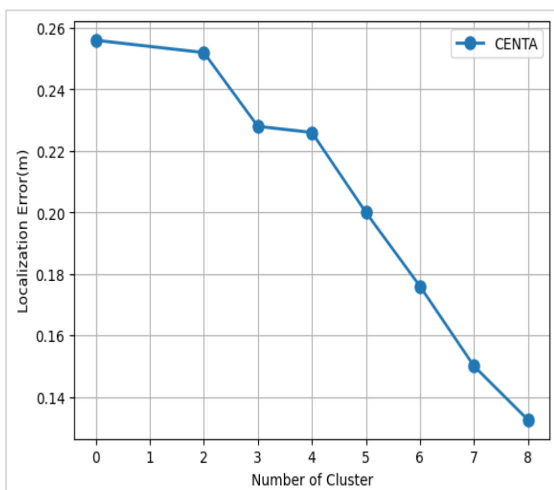

Figure 11 Localization Error(m) for CENTA

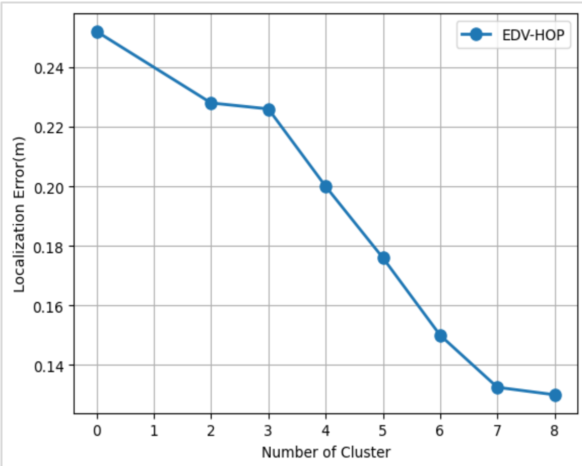

Figure 12 Localization error(m) for EDV-Hop

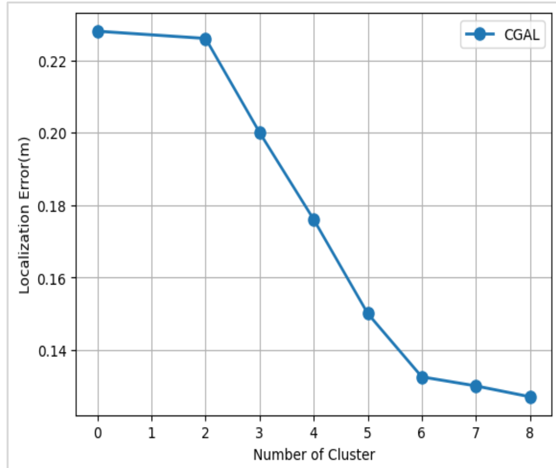

Figure 13 Localization error(m) for CGAL

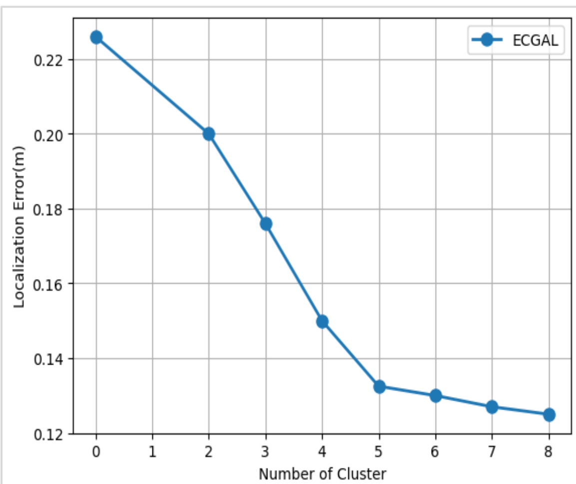

Figure 14 Localization error(m) for ECGAL

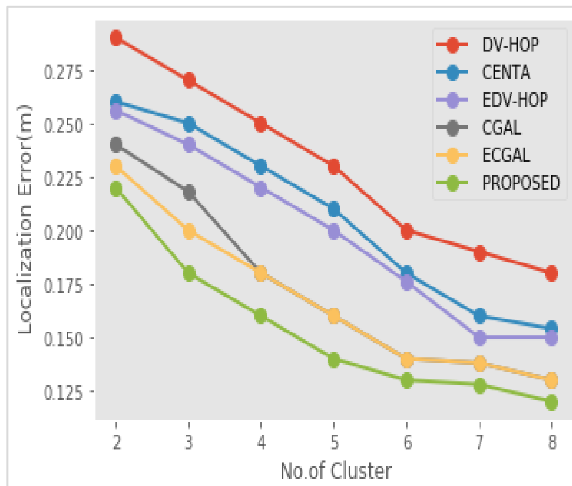

Figure 15 Localization error(m)

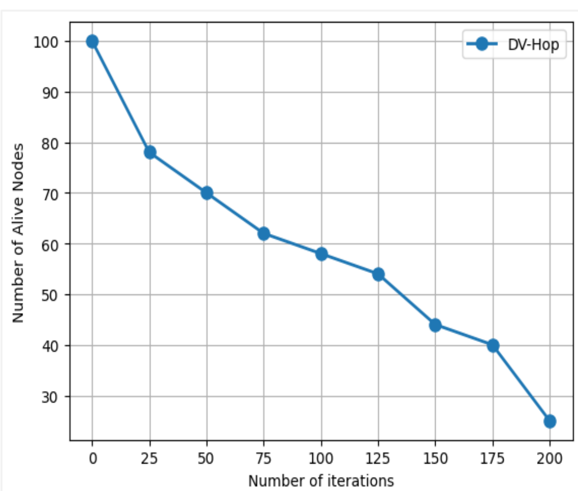

Figure 16 Number of alive nodes Vs. Number of Iteration (DV-Hop)

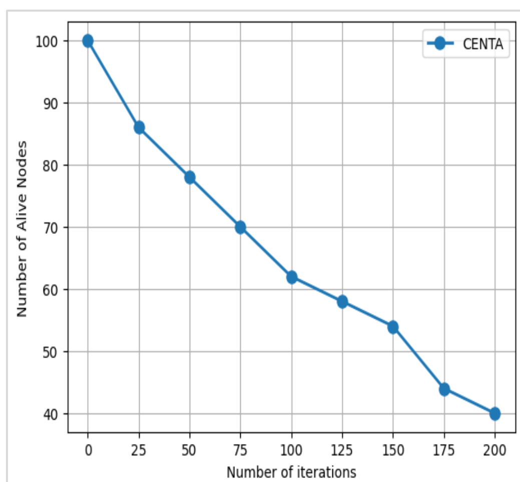

Figure 17 Number of alive nodes Vs. Number of Iteration (CENTA)

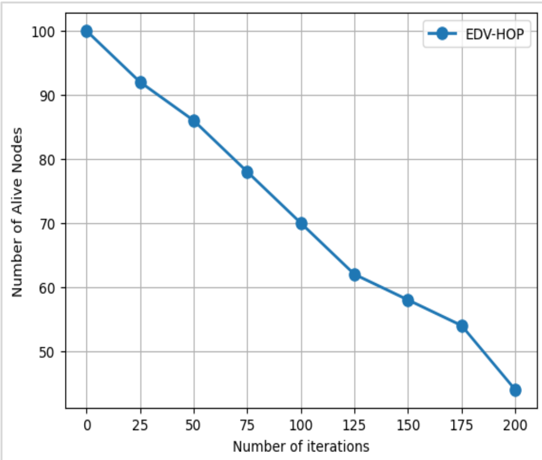

Figure 18 Number of alive nodes Vs. number of iteration (EDV-Hop)

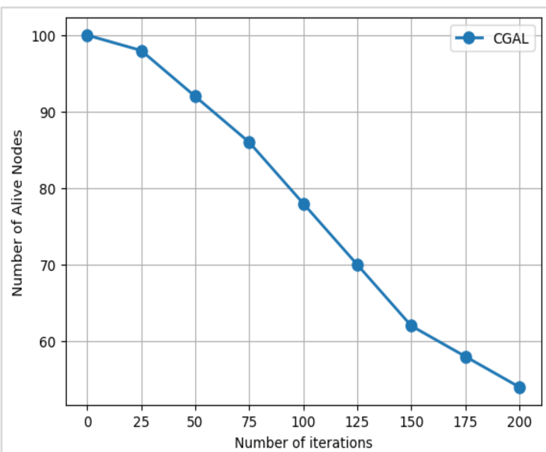

Figure 19 Number of alive nodes Vs. number of Iteration (CGAL)

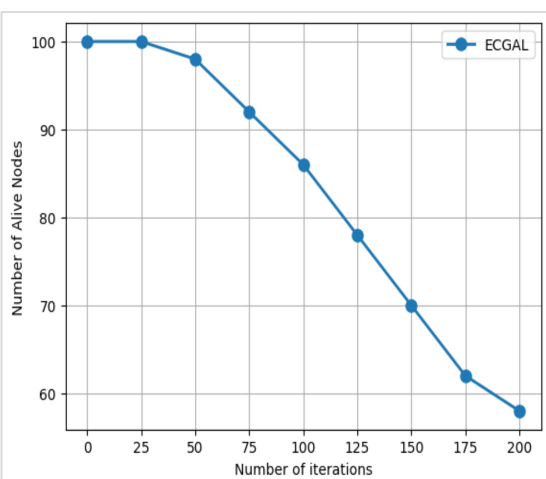

Figure 20 Number of alive nodes Vs. Number of Iteration (ECGAL)

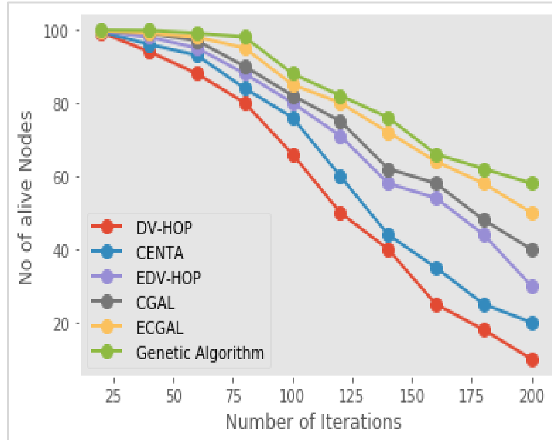

Figure 21 Alive node comparison of other algorithms

The distance between the edges is denoted by defining w1, w2, and w3 as the fitness function's weight coefficients, which measure the fitness function's contribution to each of the other sub-functions. A complete list of abbreviations is summarised in *Appendix I.*

5.Conclusion and future work

The proposed GA-based approach for positioning challenges demonstrates significant output improvements. This method enhances the localization reconstruction, enabling rapid tracking of the location of unknown sensor nodes. Whenever unknown sensor nodes appear in a location, the anchor nodes provide support. Conversely, even if this is not the case, identified nodes unnecessarily surround the unlocalized sensor nodes, contributing to an accurate and energy-efficient WSN by distributing energized nodes at random. The proposed method significantly improves performance, achieving an energy saving of 92% as demonstrated by simulation results. These results are also benchmarked against other algorithms, with the GA approach showing a more energy-efficient strategy compared to other clustering methods. The simulation outcomes highlight the goal of achieving high accuracy in node location extraction, with a low location error.

For future work, we plan to expand the coverage deployment area to either 500×500m² or 1000×1000m² and include more sensor nodes. By employing GA, we anticipate achieving a more energy-efficient strategy with higher accuracy in extracting node locations and reduced location error. While focusing on these parameters, we also aim to address the mobility aspects of WSNs to further enhance overall performance.

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None.

Conflicts of interest
The authors have no conflicts of interest to declare.

Data availability
Not applicable.

Author's contribution statement
P. Sakthi Shunmuga Sundaram: Experimental investigation, Writing – original draft, Writing – review and editing. **K. Vijayan:** Problem conceptualization, writing – review and editing.

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P. Sakthi Shunmuga Sundaram, is a Full-Time Research Scholar in the Department of Electronics and Communication Engineering at the College of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, Chennai, Tamil Nadu 603203, India. He earned his Bachelor's degree in Electronics and Communication Engineering from Dhanalakshmi College of Engineering, Chennai, affiliated with Anna University in 2007. He completed his Master's degree in Applied Electronics at Sri Muthukumaran Institute of Technology (SMIT), Chennai, also under Anna University, in 2011.
Email: sp8941@srmist.edu.in

K. Vijayan is currently serving as an Associate Professor (Grade II) in the Department of Electronics and Communication Engineering at the College of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, Chennai 603203, Tamil Nadu, India. His research focuses on Wireless Sensor Networks, Network Routing Algorithms, and the Internet of Things. He completed his Bachelor's degree in Electronics & Communication Engineering at Mahindra Engineering College, affiliated with Madras University, in 2001. He earned his Master's degree in VLSI from Anna University, Chennai, in June 2003. He finished his research and was awarded a doctorate in Electronics & Communication Engineering from VELS University in 2018.
Email: vijayank@srmist.edu.in

Appendix I

S. No.	Abbreviation	Description
1	AT	Arrival Time
2	CENTA	Centroid Localization Algorithm
3	CGAL	Clustering In Genetic Algorithm Localization
4	CLPSO	Comprehensive Learning Particle Swarm Optimization
5	DTI	Dissimilarity Time Influx
6	DV-HoP	Distance Vector Hop
7	ECGAL	Energy-efficient clustering and Localization Centered on Genetic Algorithm
8	EDV-HOP	Enhanced Distance Vector HoP
9	EEDAM	Energy-Efficient Data Aggregation Mechanism
10	EPTT	Estimated Position in Triangle Test
11	FA	Firefly Algorithm
12	FPA	Flower Pollination Algorithm
13	GA	Genetic Algorithm
14	GPS	Global Positioning System
15	GUI	Graphical User Interfaces
16	HCE	Host Card Emulation
17	GWO	Grey Wolf Optimizer
18	IDE	Integrated Development Environment
19	IoT	Internet of Things
20	LoRa WAN	Long-Range Wide Area Networks
21	MCSS	Maximum Coverage Sets Scheduling
22	NP	Non Performing
23	PSO	Particle Swarm Optimization
24	QKD	Quantum Key Distribution
25	QoS	Quality of Service
26	RSS	Received Strong Signal
27	WCL	Weighted Centroid Localization
28	WSN	Wireless Sensor Network