International Journal of Computer Networks and Applications (IJCNA)
DOI: 10.22247/ijcna/2023/223312 Volume 10, Issue 4, July – August (2023)

RESEARCH ARTICLE

Prediction Model to Analyze Source Node Localization Using Machine Learning and Fault-Tolerant in Wireless Sensor Networks

P. Sakthi Shunmuga Sundaram
Department of Electronics and Communication Engineering, College of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, Chennai, Tamil Nadu, India.
sp8941@srmist.edu.in

K. Vijayan
Department of Electronics and Communication Engineering, College of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, Chennai, Tamil Nadu, India.
vijayank@srmist.edu.in

Received: 16 May 2023 / Revised: 23 July 2023 / Accepted: 02 August 2023 / Published: 31 August 2023

Abstract – Recent technological developments include wireless sensor networks in modern and intelligent environments. Finding the localization of the sensor node is a problem in the research community field. Localization on a two-dimensional plane, a key focus in WSNs, is to maximize the lifespan and overall performance of sensor nodes by minimizing their energy consumption. The compiled data that base stations receive from packets.in wireless sensor networks can be used to make decisions with the help of localization. A cost-effective method of solving the problem is not the Internet of Things with GPR tracking sensor zones. There are several approaches to locating wireless sensor networks with unclear sensor locations. The main challenge lies in accurately determining the location of the base station's sensor node with a minor localization error during wireless communication. The proposed method, Distributed clustering Distance Algorithm (DCDA) using machine learning, considers the distance estimation error, location in accuracy, and fault tolerance issue with WSNs. According to the findings, the average localization error is 11% and 11.3%, respectively. For anchor nodes 20-80 and 200-450. As a result, when compared to contemporary methods of localization with centroid weighted algorithm (LCWA), Distance vector hop algorithm (DV-Hop), Coefficient for reparation algorithm (CRA), and Weighted Distributed Hyperbolic algorithm (WDHA) methods, the demonstrated Distributed clustering Distance Algorithm (DCDA) gives greater accuracy. According to the experimental results, the suggested algorithm significantly improves the number of alive nodes compared to the LBCA and G. Gupta FT algorithms. Specifically, the proposed algorithm achieves a remarkable 96% increase in active and functional nodes within the wireless sensor network.

Index Terms – Clustering, Distributed Clustering Distance Algorithm (DCDA), Wireless Sensor Network, Node Localization Error, Fault-Tolerant, Machine Learning.

1. INTRODUCTION

Various techniques can achieve node localization in WSNs, such as GPS-based localization: This technique uses GPS-enabled nodes to determine their locations and transmit this information to other nodes in the Network. However, GPS-based localization may not be suitable for indoor or underground environments where G.P.S. signals are weak or unavailable. Figure 1 shows the Basic Wireless Sensor Network architecture. Range-based localization: This technique uses the distance between nodes, which can be estimated using signal strength or time-of-flight measurements, to determine their locations. Range-free localization: This technique uses information such as the connectivity or coverage of the nodes to estimate their locations without measuring distances directly. Node localization is an essential aspect of WSNs, as it enables efficient data collection and analysis, improves network performance, and enables applications such as target tracking and environmental monitoring. Recent node localization literature has referred to node positioning as a novel technology [1]. An exemplary node localization strategy is essential for wireless sensor networks (WSNs) to be accurate and efficient [2]. A collection of multiple sensor nodes makes up a wireless sensor network. Dispersed throughout a region to monitor the area of interest [3]. Applications are worthless without the precise position data from the sensor node in the WSNS [4]. The proposed algorithm draws inspiration from existing protocols: Low Energy Adaptive Clustering Hierarchy (LEACH) and Quadrant Cluster-based LEACH (Q-LEACH). Its primary focus is minimizing energy usage and enhancing network coverage in a wireless sensor network [5]

RESEARCH ARTICLE

since a node's position can be ascertained in several ways [6]. Wireless bandwidth and power availability restrict the numerous rounds of tiny nodes that comprise WSNs. This Network can serve various purposes, such as measuring phenomena, monitoring areas, and facilitating industrial automation. For the Gaussian Elimination method [7], node localization estimation is crucial. ESNs, which transmit both small-and large-scale messages, comprise several sensor nodes. With the development of electronic technology WSNs can do all kinds of processes like controlling and monitoring, etc. [8]. Node localization is crucial to many network applications [9-11]. One of the issues in WSNs is node location and energy consumption. Sensor nodes' processing and computation capacities are constrained by their battery life. As a result, optimizing energy efficiency and employing power-saving techniques become crucial factors in designing and operating wireless sensor networks effectively. As sensor nodes need energy to process, sense, and store data, packet transmission is an essential WSNS activity [12-15].

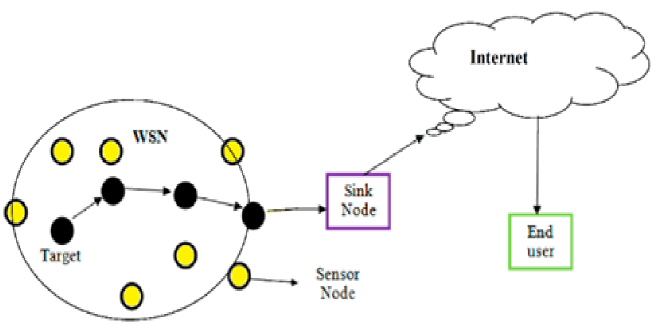

Figure 1 Basic Wireless Sensor Network Architecture

The industrial revolution concept has witnessed exponential growth in advancements, primarily fueled by the Internet of Things (IoT) coupled with wireless sensor networks [16]. This powerful combination has revolutionized industries across the globe, enabling enhanced data collection, real-time monitoring, and seamless automation processes. Integrating IoT with wireless sensor networks has proven to be a transformative force, driving efficiency, productivity, and innovation in various sectors, from manufacturing and logistics to healthcare and agriculture. As this technology continues to evolve, it holds the potential to reshape industries further and enhance our daily lives with intelligent, interconnected systems that optimize resource utilization and decision-making. Can detect the surroundings, and gather essential facts [17]. Because of the crucial platform for data exchange and sense, the Internet of Things (IoT) primarily focuses on it [18]. WSNS provides the framework for the expanding IoT, which spans various industries and fields [19]. For instance, multiple situations call for deploying intelligent products like wearable technology, camera systems, and sensor devices. Other uses for Smart devices include agribusiness, intellectual communities, cutting-edge medical care, and military service [20-21]. They are becoming more common in wireless communication. The multi-gateway clustered sensor network is shown in Figure 2. This network architecture involves the deployment of multiple gateways strategically positioned to manage and aggregate data from clusters of sensor nodes. Such a configuration enables efficient data transmission, load balancing, and enhanced network scalability, making it suitable for large-scale IoT applications and ensuring seamless communication across the entire sensor network. These nodes with dual functions-sensing and rounding have constraints on energy use and distributed auto-organizing features [22].[23]. According to projections, one trillion sensors will be installed worldwide [24]. As a result, a tremendously large amount of data should collect from a diverse and broad spectrum of WSNs [25]. Therefore, there is a constant pressing need to address and offer an innovative solution parallel to this increase in diversity and relevance. Data reliability, correctness, and integrity should be good, especially while working in risky contexts [26]. The ability of a network to provide a desired and necessary level of functionality and accurate data in the presence of problems is known as fault tolerance [27]. Finding the mistakes that occur in the Network requires well-organized fault detection. The fault tolerance framework comprises the problem identification, diagnosis, and correction procedures [28].

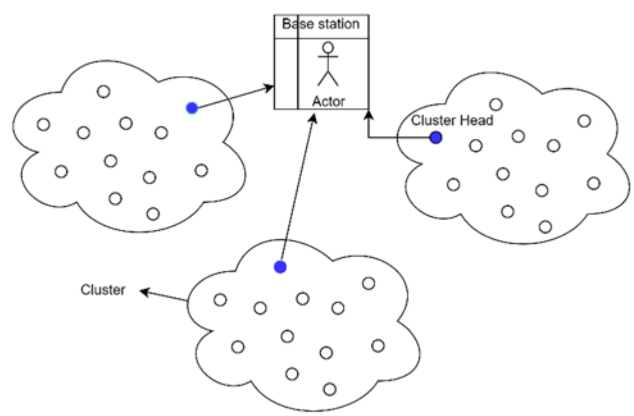

Figure 2 Multi-Gateway Clustered Sensor Network

Sensor nodes should collect and distribute the data distant throughout challenging environments in wireless sensor networks (WSNs). Nodes' locations are not always known in advance and with precision [29]. The fault is a significant difficulty for WSNs because deploying the network nodes is challenging settings. Errors in sensor networks characterizing in different ways. Three tiers: sensor nodes, clustering (networks), and base station (BS). In various ways, they can generally be divided into three levels: sensor nodes, clustering (networks), and base station (BS) [30]. The correct data want

RESEARCH ARTICLE

to transmit to the destination in WSNs for operation or decision-making. Hence the Network must be fault-tolerant [31]. The general performance of networks should not be impacted by malfunctioning nodes thanks to fault tolerance and reliability. In Wireless Sensor Networks (WSNs), the constrained energy of individual nodes poses a significant challenge. To address this issue, hierarchical routing methods have emerged as one of the most effective approaches for achieving energy efficiency, balancing energy consumption, and extending the overall lifespan of the Network [32]. Providing ways to reduce energy use improves fault tolerance essential, considering the issues facing WSNs. This work proposes a distributed clustering algorithm for fault-tolerant (DCAFFT) [33].Additionally, using residual energy results in less clustering than other algorithms and less latency and overhead [34]. The duty cycle approach is used in cluster members in the suggested manner when grouping the nodes. The power sources for the sensor nodes are limited and permanent. Energy is a significant restriction of the Network—clustering method topology technique used to increase the scalability of WSNs and lower energy usage. The selection of a cluster head uses more energy due to an increased workload from data collecting and aggregation. The proposed method, Distributed clustering Distance Algorithm (DCDA) using machine learning, will solve the wireless sensor networks challenges like distance estimation error, location in accuracy, and fault tolerance issues with WSNs.

1.1. Organization of the Paper

The subsequent sections of this paper are structured as follows:

Section 2 conducts a comprehensive review of the existing literature pertaining to node localization and faculty tolerance in wireless sensor networks. In Section 3, various types of related algorithms and the fault-tolerance mechanism are discussed. Section 4 presents the Proposed Distributed Clustering Distance Algorithm (DCDA) for Node Localization, while Section 5 introduces the Proposed Distributed Clustering Distance Algorithm (DCDA) for fault tolerance. The efficacy of the proposed approach is evaluated in Section 6, and finally, Section 7 provides the concluding remarks for the paper.

2. LITERATURE REVIEW

Wireless Sensor Networks (WSNs) play a crucial role in the Internet of Things (IoT), but they face challenges related to node localization, data aggregation, and energy efficiency. To address the node localization issue, researchers have proposed an innovative algorithm called Kernel Extreme Learning Machines based on Hop-count Quantization (KELM-HQ). This novel approach aims to enhance node localization in WSNs by harnessing the capabilities of Kernel Extreme Learning Machines, a powerful machine learning technique. By integrating hop-count quantization techniques into KELM, the algorithm seeks to improve the accuracy and efficiency of node localization [1]. Whether on a large or small scale, localization in WSNs has variations, but the Network's primary distinguishing feature is its multi-hop topologies. This research study employs an energy-efficient optimization approach DEEC-Gauss is an innovative approach that seeks to enhance energy efficiency and clustering in wireless networks. By integrating the Gaussian elimination method with the DEEC protocol, this algorithm aims to optimize the clustering process and improve overall network performance. This integration enhances energy efficiency while achieving optimal results in wireless networks [2]. To extend the lifespan of WSNs, Abdulrahman, Supriadin, and Fahmi suggested using a method of low-energy adaptive clustering from end to end that has been adjusted (ME-LEACH). The results showed that, in terms of stability and throughput, the ME-LEACH method performed better than the suggested algorithm [3]. WSNs must be more cost-effective and have access to precise location data. Furthermore, the clustering algorithms method is compatible with the hierarchy of communication algorithms employed in wireless sensor networks (WSNs)[4]. Heinzelman, Chandrakasan, and Balakrishnan used the low energy adaptive clustering method, or LEACH, at the first level of WSNS algorithms, and others have proposed a variety of algorithms to achieve clustering and node localization [5]. A mobile beacon was randomly placed throughout the area of interest (R.O.I.). To tackle the issues of node localization and energy conservation in wireless sensor networks (WSNs), researchers and engineers are actively working on innovative methods and strategies. These efforts aim to enhance the accuracy of node positioning, enabling precise tracking of sensor nodes' locations within the Network.
the approach employed the PRISMA method, which is a standardized and widely recognized technique for conducting systematic reviews and meta-analyses in academic research. By following the PRISMA guidelines, the researchers aimed to ensure the selection and inclusion of relevant articles that meet specific criteria and adhere to rigorous reporting standards. This systematic approach enables the extraction of high-quality and reliable information from the selected articles, contributing to a comprehensive and well-structured review of the topic at hand. This method ensured a systematic approach to gathering and analyzing the available literature [6]. Given the different kinds of line-of-sight nodes, distance measurement is another important aspect that can potentially alter localization. MA*-3DDV-Hop is a novel approach that seeks to achieve more precise and reliable node localization in wireless sensor networks. By combining the strengths of the improved A* algorithm and the 3DDV-Hop algorithm, the method strives to better estimate the number of hops between nodes and correct any inaccuracies in measuring the average distance per hop. This optimization process enhances the

overall accuracy and effectiveness of node localization, making the algorithm a promising solution for practical applications in wireless sensor networks by integrating these techniques, the proposed algorithm aims to improve the accuracy and efficiency of node localization in wireless sensor networks. [7]. Researchers have proposed numerous node localization adjustments for unevenly distributed nodes to balance power consumption and extend network lifetime. A prevailing challenge in contemporary times is the packet delivery time, prompting the conduction of multiple research projects over the years aimed at enhancing and optimizing this aspect. In this research paper, the authors propose and evaluate an Energy Efficient Emergency Rescue Scheme (EEERS), which facilitates high-speed and minimal-delay data transfer within the IoT field. The simulation results demonstrate that the Energy Efficient Emergency Rescue Scheme (EEERS) achieves significant improvements in an emergency rescue IoT environment, including a reduction in end-to-end delay by 30–35%, an increase in throughput by 40–42%, a reduction in energy consumption by 50–55%, a decrease in packet loss by 60–65%, and an enhancement in packet delivery ratio by 36–40% [8]. The choice of CH and gravitational search employed both strategies for optimizing ant colonies and particle swarms. It will mainly use for routing from the sink to the cluster head (CH). These techniques were used for better system performance, leading to the best clustering and hop path choice. A triple mobile anchor and three mobile sensors arranged in a triangle were used for localization to identify the unidentified sensor nodes and get signal strength indicators (RSSI). Similarly, like this, it was suggested to use social networks with small-world (S.W.) characteristics to analyze the position of the node and time synchronization problems over the small world in wireless sensor networks, which helped to produce better findings than cutting-edge normal WSNs. The findings indicate that the ME-LEACH method outperforms SEEC and EERRCUF in terms of both stability and throughput, demonstrating a higher and more consistent throughput. Additionally, ME-LEACH exhibits a 35.2% improvement in network lifetime compared to the E-LEACH algorithm. [9]. Like this, a localization method called Optimal Distance Range free (O.D.R.) method will reduce the quantity and size of hops without increasing the number of the communication channel. Sizes can be determined with the aid of DV-Hop the centroid is calculated using the anchor nodes that are the least distant [11]. The primary research areas for localization approaches include energy, clustering tactics, and longevity enhancement. Additionally, the capabilities close to using node resources and sensor nodes have raised the complexity of the Network, which has thrown the CH out of balance and led to related problems. It was suggested to use a power methodology to balance CH loads. To demonstrate the notable performance of significant NLOS mistakes, Cheng et al. Applied the localization on an indoor approach based on legally obtained collective prediction data for wireless sensor networks. The presented paper introduces the WRCDV-Hop method, an enhanced version of the widely recognized DV-Hop localization algorithm, offering fourfold improvements. Notably, WRCDV-Hop's departure from the traditional discrete approach to hop count measurement allows for more precise localization and better energy efficiency. These advantages make it an attractive choice for node localization in wireless sensor networks, where accuracy and energy conservation are critical factors for the successful operation of the Network.[35]. Due to the positive variance, some of the measurement data obtained from the NLOS are unreliable. By combining the principles of Cat Swarm Optimization, parallelization, compactness, and innovative communication strategies, the Parallel Compact Cat Swarm Optimization (PCCSO) algorithm aims to achieve superior performance in solving complex optimization problems. Its ability to efficiently explore the search space and incorporate diverse communication strategies makes it a promising candidate for a wide range of optimization applications. PCCSO offers several advantages, including an improved local search capability and reduced computer memory requirements. [36]. Hao et al. employed the Voronoi and vector support machine approach. The PF-AKF method presents a promising approach for enhancing state estimation accuracy in Wireless Sensor Networks by integrating Polynomial Fitting and the Adjusted Kalman Filter to provide more reliable and efficient solutions for various applications in WSNs. The aim of the proposed method is to improve the accuracy of data estimation in WSNs by combining polynomial fitting and the Kalman filter [37] to enhance the performance and accuracy of localization. Localization using a single anchor node was used. The objective of this article is to optimize the location accuracy of node positions in a wireless sensor network (WSNS) by analyzing existing literature. In order to achieve this, the article proposes a novel node location algorithm based on Voronoi diagrams and support vector machines (SVM). The proposed algorithm is evaluated through both simulation and natural environment experiments, and the results are thoroughly analyzed. The findings demonstrate that the algorithm outperforms two other localization algorithms, namely ORSS-VBLS and W-VBLS, in terms of location accuracy for the target node. The next step in this research is to further investigate and analyze the algorithm's performance in large-scale and complex environments. This will involve conducting experiments in scenarios that more closely resemble real-world WSNS deployments, where factors such as obstacles, varying signal strengths, and interference can impact location accuracy. By examining the algorithm's behavior in such conditions, researchers can gain insights into its robustness and suitability for practical applications [38]. Sruthi and Sahadevaiah. This paper introduces a novel localization algorithm for wireless sensors, based on Artificial Neural Networks (AN). The proposed approach conducted extensive simulations to test their method, and the results showed that their localization algorithm outperformed the current best methods available. In other words, their approach was more accurate and efficient in determining the precise location of objects or devices compared to existing state-of-the-art techniques. This has significant implications for various applications that require accurate localization, such as navigation systems, tracking devices, and location-based services [39] also employed the effective paradigm technique. The table below provides a list of significant recent articles that demonstrates gaps in the literature and how this research study contributes to it. the proposed HC-RDA algorithm offers an enhanced and more effective way to solve the localization problem for unknown nodes in wireless sensor networks, considering the trade-offs between distance, received signal strength, and energy consumption. By integrating these two algorithms, the HC-RDA algorithm offers an effective and efficient solution for the localization of unknown nodes in the wireless

Sensor network [40]. By incorporating these features, the Cluster Arrangement Energy Efficient Routing Protocol (CAERP) strives to achieve a more sustainable and stable WSN. The protocol's focus on network lifetime enhancement, energy efficiency, and load balancing contributes to a reliable and prolonged operation of the wireless sensor network, making it a promising solution for various WSN applications and scenarios. The CAERP protocol aims to optimize these key factors by organizing the Network into clusters and employing energy-efficient routing strategies within each cluster. By leveraging cluster arrangements, CAERP can effectively distribute the network load, CAERP provides a promising solution for addressing the energy-related challenges in WSNs. Its focus on minimizing energy consumption, improving energy efficiency, and promoting load balancing results in a more sustainable and reliable wireless sensor network, extending its overall lifetime and enhancing its performance. This makes the protocol a valuable and practical option for various WSN applications where energy conservation and efficient resource management are crucial factors [41]. This study aims to achieve control over normal and isolated states in a network. To address congestion, the congested node utilizes link permutations and observes transition probabilities for routing decisions. The proposed method allows nodes in the Network to monitor their states and take appropriate actions in response to immediate rewards and desired outcomes within a specific time period. The simulations conducted using the NS2 simulator demonstrated that this approach was effective in improving forwarding estimates, especially in scenarios involving overloaded and isolated nodes. These findings highlight the efficacy of the proposed method in managing congestion and maintaining network stability [42]. To alter the current localization, various techniques are employed, identifying the redundant node, and making that node sleep for some time interval and wake up again using the sleeping node scheduling method based on redundant node energy reduction is a strategy designed to conserve energy in WSNs by putting redundant nodes into a sleep mode at specific intervals. This method improves energy efficiency, prolongs the network lifetime, and helps to maintain the Network's functionality while minimizing energy wastage. It will improve the lifetime of the wireless sensor network [43]. Gathered knowledge about the other WSNS nodes, their locations, and the distances between them, which will be used to develop the localization algorithms. Several research initiatives in the field of sensor networks have inspired the work. Research is being done on both—sensor networks' hardware and software components. The size and functionality of sensors have taken on a new dimension because of initiatives like intelligent dust, WINS, and Pico Radio. Several research groups have concentrated on problems including sensor coordination, energy-aware routing, and energy conservation by just turning on a few nodes. This paper focuses on exploring various types of algorithms and conducting a comparative analysis of their accuracy in target detection. The research study serves as a comprehensive and informative resource for those interested in understanding the workings of these algorithms and their relevance in the respective field of study. The graphical models add visual clarity and enhance the presentation of the findings, making the research more accessible to a broader audience. By systematically comparing and evaluating the performance of these algorithms, the study aims to contribute to the understanding of target detection methodologies. The ANN algorithm gives the best performance compared to other algorithms [44]. Because sensors are often battery-operated and have a limited energy source. For the effective selection of a cluster head, a variety of clustering techniques have been proposed, including random, the lowest cluster I.D., and the highest degree of connection. However, if the cluster's workload is not evenly distributed, it may increase communication latency, insufficient targets, event tracking, and, ultimately, gateway failure. They propose a multi-gate architecture to distribute the load among the clusters and organize the network gateways around high-energy gateways. Additionally, these methods emphasize the system's dependability and fault tolerance. This manuscript presents the Weighted Path Rediscovery (WPR) routing algorithm, which is designed to enhance routing decisions in Wireless Sensor Networks (WSNs). The primary objective of this algorithm is to address two key issues: backtracking and looped routing. By preventing backtracking and curtailing looped routing, the WPR routing algorithm aims to improve the overall efficiency and effectiveness of data routing in WSNs. The introduction of the Weighted Path Rediscovery (WPR) routing algorithm in WSNs not only prevents backtracking and looped routing but also leads to improved

RESEARCH ARTICLE

packet transmission quality and reduced routing complexity. By optimizing the path selection process, the algorithm ensures that packets are transmitted with higher reliability and fewer errors. Moreover, by minimizing routing complexity, the WPR algorithm reduces the computational overhead associated with routing decisions, resulting in more efficient network operations. [45]. When a cluster head fails, either redundant hardware is required to replace it, or the role is moved to a different node, necessitating a complete system reconfiguration. Regularly picking Project like LEACH increase the system's redundancy by generating a cluster head from the Network's sensor. But are burdened by re-clustering overhead. Think that if efficient recovery is built into the design, significant performance gains can be made. During runtime, faults should be found and treated. Many studies have been done on fault analysis and modeling. This research describes a runtime recovery system to recover sensors from failed clusters and identify gateway issues. Network Localization and Mobility: Localization of sensor nodes, especially in outdoor environments, can be challenging due to factors like limited sensing ranges, signal propagation variations, and node mobility. Accurate node localization is crucial for various applications such as target tracking, object localization, and location-based routing. Fault Tolerance and Resilience: WSNs are vulnerable to various faults, including node failures, communication disruptions, and environmental factors. Ensuring fault tolerance, fault detection, and recovery mechanisms to maintain network resilience and reliability is an ongoing challenge. Source node localization is crucial for efficient network management, accurate data interpretation, energy efficiency, and target tracking in WSNs. It enhances the overall functionality and performance of WSNs in various applications and scenarios. By incorporating fault tolerance mechanisms into wireless sensor networks, system designers and researchers can improve the Network's robustness, reliability, and overall performance. This is especially crucial in applications where continuous monitoring, real-time data collection, and reliable communication are vital, such as environmental monitoring, industrial automation, healthcare, and disaster response systems to ensure robustness, reliability, network longevity, data integrity, scalability, and security. By incorporating fault tolerance mechanisms, WSNs can continue to operate effectively and provide accurate and reliable data in challenging environments or in the presence of faults.

3. DISCUSSING THE RELATED ALGORITHMS

3.1. Distributed Clustering (DC) Algorithm

The Distributed Clustering (DC) algorithm is a clustering protocol designed to increase the lifetime of wireless sensor networks (WSNs) by lowering the energy consumption of sensor nodes. The DC algorithm is based on the idea of forming clusters of sensor nodes with one cluster head node, which oversees gathering and transmitting data from cluster members to the base station. The algorithm works in a distributed manner, where each sensor node decides whether to become a cluster head or join an existing cluster based on a probability threshold. The probability threshold is calculated based on the sensor nodes remaining energy and the distance from the nearest cluster head. The DC algorithm uses a multi-hop communication strategy, where the base station receives the aggregated data from the cluster heads. Via other cluster heads. This contributes to lowering each sensor node's energy consumption and extending the network lifetime. The DC algorithm has been shown to outperform other clustering protocols regarding network lifetime and energy efficiency in various simulation studies. However, the algorithm's performance depends on multiple factors, such as the network size, node density, and communication range, and may need to be adjusted accordingly.

3.2. Gaussian Elimination (GAUSS) Algorithm

The GAUSS algorithm, also known as the Gaussian Elimination algorithm, is a numerical method used to solve systems of linear equations. It is a popular method used in linear algebra and is widely employed in various fields of science, engineering, and computer science. The GAUSS algorithm aims to transform a system of linear equations into a more straightforward form, ultimately leading to the determination of the values of the unknowns in the system. The algorithm involves a series of elementary row operations, such as adding multiples of one equation to another, multiplying an equation by a scalar, or swapping two equations to transform the system of equations into an equivalent system that is easier to solve. The basic steps of the GAUSS algorithm are as follows: Represent the system of linear equations as an augmented matrix, a rectangular array of numbers containing the coefficients of the unknowns, and the constants on the right-hand side of the equations. Apply row operations to the augmented matrix to transform it into a triangular form, where all the coefficients below the main diagonal are zero. This is typically done using elementary row operations to create zeros below the main diagonal, starting from the top row and working downwards. Once the augmented matrix is triangular, the values of the unknowns can be determined by back-substitution. Starting from the bottom row of the triangular matrix, the importance of the unknowns can be calculated iteratively by substituting the known values of the already solved unknowns and solving for the remaining unknowns. If necessary, the solution obtained from the GAUSS algorithm can be further verified by substituting the obtained values of the unknowns back into the original system of equations to check if they satisfy all the equations. The GAUSS algorithm is a powerful and widely used method for solving systems of linear equations, and it can also be extended to handle other tasks, such as matrix inversion and finding determinants. However, it is essential to note that the algorithm may have limitations, such as issues

RESEARCH ARTICLE

with numerical stability and computational efficiency for large systems of equations. Alternatively, methods may be more suitable in certain situations.

3.3. Gaussian Discriminant Analysis (GDA) Algorithm

GDA stands for Gaussian Discriminant Analysis. It is a classification algorithm that assumes the distribution of each class is Gaussian (also known as the normal distribution) with a shared covariance matrix. The GDA algorithm first estimates each class's mean and covariance matrix in the training data. Once these parameters have been calculated, the algorithm can use Bayes' theorem to determine the subsequent likelihood of each category given an input sample. The highest posterior probability group is then assigned to the input sample. To predict a new input sample, the GDA algorithm first computes the likelihood of the input sample for each class, assuming that the distribution of the input sample within each class follows a Gaussian distribution. The algorithm then uses Bayes' theorem to compute the posterior probability of each class, given the observed input sample. Finally, the algorithm assigns the input sample to the class with the highest posterior probability. GDA is a generative model which explicitly models each class's distribution and can be used to generate new instances of data for each category. GDA is also closely related to other classification algorithms.

3.4. Fault-Tolerance Mechanism

The method's primary goal is to provide runtime sensor recovery from clusters where the Gateway has encountered some issues. Detection and recovery are the two parts of the system. Determining whether the failed cluster's sensors must be recovered or a system fault has happened is crucial. We use a gateway consensus approach to reach a consensus on a specific system flaw. An agreement is necessary to keep the Network's synchronization regarding the state and a gateway's cardinality. The quantity of sensors that make up a gateway's cluster is known as its cardinality. Later sections show circumstances where gateways may dispute a gateway's validity and describe workarounds. A faculty-type approach to fault tolerance is the second stage. Identification and sensor recovery. Detection of gateway failure. In the system, detection comes first in the fault-tolerance process. In a sensor network, each Gateway has a distinct identity. Position informs let each Gateway know where the other cluster node of the system is located. The corresponding Gateway for each sensor determines their TDMA schedules. Usually, gateways assign sensor slots to relay data based on the amount of energy available, the tasks at hand, and the priority. An easy slot allocation for a gateway is shown in Figure 3. In a "Route Update" slot, sensors are notified of the schedule and routing details. The white places are set aside by sensors that must transmit data during that cycle, whereas the dark spaces stand in for the route update slots. Sensors supply the gateways with their energy condition and the sensed data. Gateway status is exchanged. The duration of this slot depends on the system's stability. The status exchange is scheduled using a linear decrease multiplicative increase (LDMI) technique. While linearly reducing the period when a defect is identified, LDMI lengthens the exchange period when there are no problems. This technique helps the system recover quickly from errors when it is fragile and reduces the status exchange cost when the system is steady. Status updates are both an announcement of the Gateway's presence and a heartbeat message. When no updates are received by gateway "A" from other gateways "B" after the detection phase, gateway" B" is viewed as defective by gateway "A." All Gateway must establish a consensus before recovery can start since updates may be missed if a link between two nodes fails. The most important thing to remember is that a gateway should not be written off until at least one other Gateway in the Network can connect with it. Updates must be forwarded over several hops in case of a link failure.

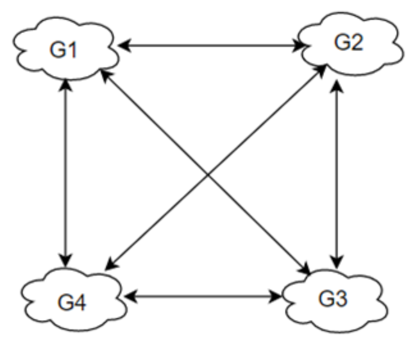

Figure 3 Fully Connected Gateway Model (Case-1)

These updates can be delivered using efficient routing, which requires upkeep and updating tables belonging to routing. Every "new" update a gateway gets is forwarded (broadcast) to every other Gateway within range. When there are no issues with the Network, this approach will add additional messages. By ensuring that each Gateway has access to the same system status information. Since every Gateway can access comparable data, a consensus is instantly achieved. None of the other gateways will receive the updates and be able to begin the recovery if a gateway has failed—fully connected gateway model (Case-1), as shown in Figure 3. To clarify the forwarding strategy, we provide two scenarios. However, the forwarding method forces the gateways to broadcast redundant status data from other gateways. They employ an "experience" based strategy to prevent this message redundancy in the absence of systemic issues. Each Gateway creates an experience of the change it receives before transferring them to other gateways. In case 1, there are no faults and a fully connected network. First, they shared their observations regarding the connectivity with other gateways. They first discussed their findings about the connectivity with more gateways. A table of experience is created after learning from the experience of earlier gateways to demonstrate the interconnection of various system nodes. The experience table for the circumstance is displayed as shown in Table 1.

Table 1 Case-1 for Experience Table

	G1	G2	G3	G4
G1	No	Yes	Yes	Yes
G2	Yes	No	Yes	Yes
G3	Yes	Yes	No	Yes
G4	Yes	Yes	Yes	No

Where: Indicates a Personal Update. One denotes the update received, while 0 means it was missed. Following the loss of the connection between gates G1 and G3, the total failure of Gateway G4, Many links, and a single full failure Mode (Case-2) as shown in Figure 4. There are multiple links and a single complete failure mode.

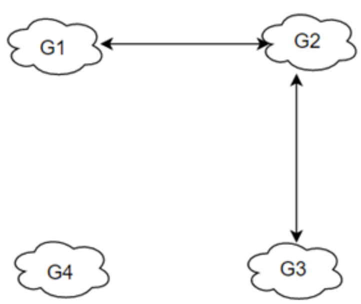

Figure 4 Many Links and a Single Total Failure Mode (Case 2)

Table 2 Condition 1

Gateways	G1	G2	G3	G4
G1	High	Pass	0	0
G2	Pass	High	Pass	0
G3	0	Pass	High	0
G4	0	0	0	0

Gateway G4 will not transmit any updates to gateways during condition 1. Displays the experience table created at gateway G2, as shown in Table 2. Gateway G2 discover after studying the experience table that neither Gateway G4 nor any of the other Gateway has sent any status updates to any of the other Gateway. This unequivocally demonstrates that G4's transmitter malfunction prevents it from sending data to other nodes. G4 is marked as having entirely abortive and extracting every sensor in its cluster is necessary. The experiences on G1 and G3 have zeros, which means their links have been unable. G2 recognizes that it must send the update to Gateway's G1, and G3 was a complete disaster. G4 cannot be confirmed unless all gateways are informed of the experience. When the Gateway is, all the updates are given to G1 and G3. Other than those from G4, they conclude that G4 has wholly failed. Recovery of the sensor, if a sensor "Sj" meets the requirements listed below, it is included in the field set "RSet" of the gateway "Gi." as shown in equation (1).

$$the\ N_j \in RSet_{Gi} \leftrightarrow \left[(R_{Gi} > d_{Nj})\nabla(R_{Nj,max} > d_{Nj>Gi})\right] \quad (1)$$

where $\boldsymbol{RN_j}$, max is the sensor S.N.'s maximum range. Each Gateway creates an additional location for recovery purposes that contains nodes that are part of its TSet but do not belong to the Gateway's cluster. It is known as a backup set (BSet).

Each node can be a part of numerous BSet but can only belong to one FSet at a time—the definition of BSet as shown in equation (2).

$$N_j BSet_{Gi} \leftrightarrow \left[(N_j \in RSet_{Gi})\nabla(N_j \ni FSet_{Gi})\right] \quad (2)$$

Every Gateway searches its BSet for the sensor when a sensor needs to be recovered. Suppose the sensor is found in the Gateway's BSet. It is recovered. When a sensor is present in more than one BSet. They consider a sensor node architecture using two nodes, gateways, and a wireless sensor network. The gateways and sensor nodes can both be manually installed. They enter the sensing region at random and then become stationary deployments. Only one Gateway can accept a sensor node if the sensor's communication range includes the gateway node. Gateways can communicate over large distances—the ability to directly interface with when compared to sensor nodes in the base station (BS). Every communication is conducted using a wireless connection and a between two nodes, and a wireless link can only be created if they are inside each other's range of communication. Due to the symmetry of wireless sensor networks, a node can compute the based on the signal received, an approximation of the distance to another node's strength.

4. PROPOSED DISTRIBUTED CLUSTERING DISTANCE ALGORITHM (DCDA) FOR NODE LOCALIZATION

Reducing localization errors in WSNs requires the development of accurate and proposed distributed clustering distance algorithms (localization algorithms), careful calibration and characterization of sensors, consideration of environmental dynamics and network geometry, and accounting for node mobility and resource constraints—the proposed Distributed Clustering Distance Algorithm (DCDA) flow chart as shown in Figure 5 and about the Distributed Cluster Algorithm discussed in section 3.1 Algorithm. Fusion of data from multiple sensors, utilization of machine learning techniques, and incorporation of error mitigation techniques, such as error modeling, error correction, or outlier detection, can also help reduce localization errors in WSNs. The Energy is distributed equally for the sensors, as shown in equation (3). Rigorous testing, validation, and fine-tuning of

RESEARCH ARTICLE

localization algorithms in real-world deployments are also essential to minimize localization errors and ensure the accurate positioning of sensor nodes in WSNs. With a network size of 100 by 100, the gradient error of the node localization calculations. I aid in the energy dissipation needed. The Bi-computation for equal nodes can begin the iteration, as shown in equation (4). To dispatch packets received to the base station and acknowledge data. Then, assuming that 10% of all sensor nodes are cluster heads or anchor nodes. To determine how much energy the transmit amplifier requires, as shown in equation (5). The anchor node identities (Hi, Gi) and Hop I,j are expected to be the number for the hop count Sent reaching the center base stations, and how to calculate the energy as shown in equation (6). As shown in equation (7) Calculate the average Hop size for sensor node distance. To Determine the average size of the Hop, where 'h' is a constant parameter,'s' and't' are variables as shown in equation (8). Anchor nodes for the entire sum are found to be the sensor localization method using weighted centroid, as shown in equation (9). Aims to implement the suggested solution utilizing the following algorithm steps.

4.1. DCDA Algorithm Steps for Node Localization

Step 1: Installation of the sensors

Step 2: Creating the network model.

Step 3: Distributing equals energy for the sensors.

$$using E_{Total} = \sum_{i-1}^{n} D_0\,(1 + x_i) = D_0((n + \sum_{i-1}^{n} x_i)) \quad (3)$$

Step 4: Bi-computation for equal nodes can now begin the iteration.

$$Bi = \frac{K_{opt}N(1+x)D_i(r)}{[N+\sum_{i=1}^{N} x_i]\nexists(r)} \quad (4)$$

Step 5: The formula for determining how much Energy the transmit amplifier requires

$$D_{TX}(l,d) = \begin{Bmatrix} lD_{elec} + l_{\varepsilon_{fs}} d^2, d < d_0 \\ lD_{elec} + l_{\varepsilon_{mp}} d^4, d \geq d_0 \end{Bmatrix} \quad (5)$$

Step 6: Moreover, the receiver's energy requirements are calculated using the following equation

$$D_{RX}(l) using D_{RX}(l) = D_{elec} \quad (6)$$

Step 7: The size to calculate the average Hop size for the distance between the sensor nodes,

$$HSA_i = \frac{\sum_{j=1}^{m}{}_{j\neq i}\sqrt{(E_J-E_I)^2+(E_j-E_i)^2}}{\sum_{j=1}^{m}{}_{j\neq i} HSAij} \quad (7)$$

Step 8: Determined the average size of the Hop, where 'h' is a constant parameter's' and't'' are variables.

$$d_{st} = HSA_h * HSA_{st} \quad (8)$$

Step 9: The anchor nodes for the entire sum are found to be the sensor localization method using weighted centroid as 'm'. (H_f, HG_f). 'M' assumed the total number of anchor nodes.$H_f = \frac{1}{mHop_{ui}}$ (7) is assumed to be the weight factor for the unknown sensor, and I am calculated from,

$$H_f = \frac{\sum_{i=1}^{m} Tw_{ih_i}}{\sum_{i=1}^{m} Tw_i} \quad , \quad G_f = \frac{\sum_{i=1}^{m} Tw_{ig_i}}{\sum_{i=1}^{m} Tw_i} \quad (9)$$

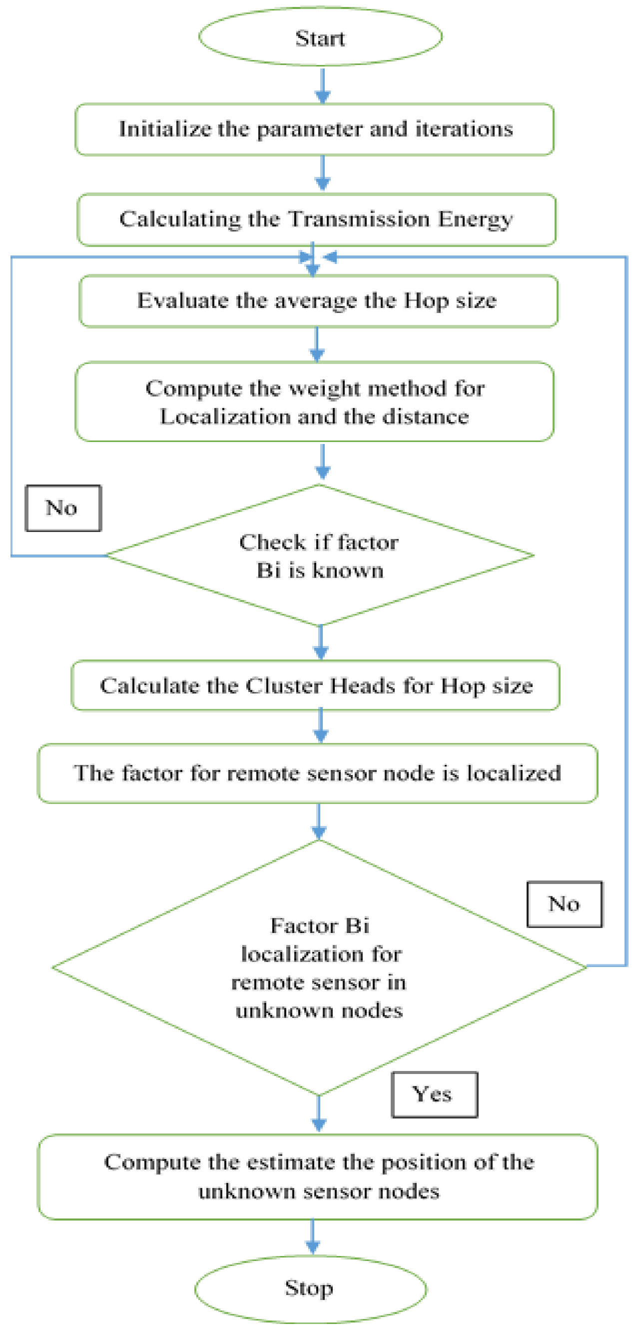

Figure 5 Flow Chart for the Proposed Method

RESEARCH ARTICLE

Standard matrix like A.X=B. The code snippet determines the Network's number of rounds and the ideal number of clusters. A 0.5j homogeneous energy value is used. At each sensor clustering point over the whole network connection. The suggested method efficiently uses the sensor node's energy resources by employing the DC-GGDA for node position. Describing an evaluation process involving the DEEC-Gauss algorithm as explained in session 3.1 and an advanced localization technique. From what you've mentioned, the evaluation metric used to compare these algorithms is the Probability of Error (PoE) is determined by dividing the localization error by the total number of nodes, with the region of interest set to "mm" meters when "m" equals 100". At the location's field centers where the base station is located. The system's specifications were a 1.90 GHZ Intel core i7-8650U processor and 2.11 GHz, with 8 G.B. of installed RAM (785 GB usable). Window 10 runs on a P.C. with a 64-bits operating system and an x64-based processor.

5. PROPOSED DISTRIBUTED CLUSTERING DISTANCE ALGORITHM (DCDA) FOR FAULT-TOLERANT

The Proposed Distributed Clustering Distance Algorithm (DCDA) for Fault-Tolerant (DCDA-Fault-Tolerant) is as follows, every sensor node and Gateway begins with a bootstrapping process, during which the BS gives each of them a unique I.D. Then, at a specific power level, BS transmits a HELP message. By using the received signal intensity and this method, each Gateway may determine the approximate distance to the BS [18] [19].it aids in the proper power level selection for the gates while interacting with the base station (BS). A TDMA schedule is additionally made available to gateways for M.A.C. layer communication. Gateway transmits a HELP message throughout a sensor node's communication range during setup. The gateway I.D., remaining energy, and base station distance are all included in the HELP message. A sensor node Ni joins Coset if at least one HELP message has been sent to it, subsequently predetermined timeout; then it will join UnCOset. The 'HELP' message is broadcast via the Ni and Ni UnCOset sensor nodes as a backup. As a result, sensor node Sj joins the reserve set.it is a neighbor of Ni and a Coset (Ni) member. The maximum amount of energy from the backup set (Ni) is used by Ni, as shown in equation (10).

$$E_{residual}(N_j) = Max\{(E_{residual}(N_{k)}|\forall N_k \in BSet(N_{i)})\} \quad (10)$$

The results depend on the cost function, as shown below. The sensor nodes j,j set, N N CO join a CH, Gi cluster head cost for Nj shall be denoted by CH cost (Gi, Nj). Considering the following parameters when defining the cost function.

1. The cluster head with the highest remaining, one that sensor nodes should join, as shown in equation (11).

$$CH_{Cost(G_i,N_j)} \propto E_{residual}(G_i) \quad (11)$$

2. Since non-CH sensor nodes expend the most energy connecting with their CH, the sensor node should join the closest CH The likelihood of joining increases as distance decreases, as shown in equation (12).

$$CH\_Cost(G_i, N_j) \propto \frac{1}{Dist(N_{j,}G_i)} \quad (12)$$

3. Unlike sensor nodes, gateways can connect across long distances and can communicate with base station directly.As a result, CHs' cluster membership should be lower than that of the CHs that are closer to the BS, as shown in equation (13). Otherwise put,

$$CH_{Cost}G_i, N_j \propto \frac{1}{Dist(G_i,BS)} \quad (13)$$

Equations 10, 11, and 12 are combined how to provide as shown in equation (14).

$$CH\_Cost(G_i, N_j) \propto \frac{E_{residual}(G_i)}{Dist(N_{j,}G_i)*Dist(G_i,BS)} \quad (14)$$

The simplified equation is shown in equation (15).

$$ie., CH_{Cost}(G_i, N_j) = K * \frac{E_{residual}(G_i)}{Dist(N_{j,}G_i)*Dist(G_i,BS)} \quad (15)$$

K1 is a proportionality constant. Similarly, use the sensor nodes' weight value for comparison. Because of this, can assume K1=1 and continue to pursue the goals without losing generality.

Therefore how it will become, as shown in equation (16),

$$CH_{Cost}(G_i, N_j) = \frac{E_{residual}(G_i)}{Dist(N_{j,}G_i)*Dist(G_i,BS)} \quad (16)$$

The other form of representation as shown in equation (17).

$$CH\_Cost(G_i, N_j) = Max\left\{CH_{Cost(G_k,N_j)}\middle|\forall G_k \in CRCH(N_j\right\} \quad (17)$$

The sensor nodes (N_i, N_jCO_{set}) use equation (4.5) to determine which CH they want to join before delivery. Additionally, it guarantees the radio all but their respective sensor node's components will be turned off. Transmit moment, as a result, uses less energy. Each sensor node simultaneously executes this method. Fault Tolerance with increasing strain and limited energy during the steady state period, the CHs may malfunction at any round. The issue can be identified when the member sensor nodes are ineffective.

5.1. DCDA Algorithm Steps Fault-Tolerance

Step 1: Si sent a HELP signal out within the range

CRCH(Ni)= {};

BSet (Ni)= {};

Step 2: If (after obtaining a response from Ni)

RESEARCH ARTICLE

(reply is from gateways G.W.)

Ni becomes the elements of Coset

CRCH(Ni)=CRCH(Ni) ∪ Gw

else if (from sensor node N.J., this response)

BSet (Ni)=BSet (Ni) ∪ Nj

endif

endif

end while

Step 3: if (Ni ∈ UnCOset&&|BSet (Ni)|≠0), then Si uses Nj from BSet (Ni) as transmit with

The highest residual energy to send the data to the CH

else

Ni calculates the cost of all CHs from CRCH(Ni).

Endif

Stop.

The adjacent identical sensor nodes in a cluster can determine if a CH is malfunctioning by receiving any data acknowledgment reception or synchronization message sent by the cluster head in the form of an ideal. The sensor nodes Nj and N_j neighbor (N_i) reply to the statement 'HELP.' Again, it will change from UnCOset to Coset elements later, receiving responses from the Cluster head. All the Ni, Ni UnCOset, and N_i Reset Backup Set (BSet) S nodes as the relay with the most significant remaining energy required to send the info to the cluster head.

6. RESULT AND DISCUSSION

Mainly the Proposed Distributed Clustering Distance Algorithm (DCDA) for Node Localization and fault tolerances. The proposed method DCDA has been developed in the python 3.6 (64-bit) platform simulation environment and the system for optimal performance, and it is recommended to have at least 4 G.B. However, using 2 G.B. of RAM as a minimum requirement is still feasible—the simulation parameters as shown in table-3. To compare the performance of innovative clustering methods like LCWA, Distance Vector HoP, CRA, and WDHA, you would need to thoroughly evaluate specific datasets and performance metrics relevant to clustering algorithms. These evaluations often involve comparing accuracy, clustering quality, scalability, and computational efficiency. Researchers and practitioners in data clustering can perform such assessments to determine the most suitable method for their particular application or domain. The scalability, error performance, and mobility model are assessed using the localization with centroid weighted algorithm (LCWA) setup process. Since the LCWA approach does not ask for help and relies on readily available RSSI data, they are well suited for localization.

Table 3 Simulation Parameters

Parameter	Value
Total number of nodes	2000
Field Coverage	2000*2000 square meters
The energy level in the initial	0.5J
Size of the message	5000 Bits
Number of Gateways	50
Initial Energy	10 joules
Number of clusters	5
Maximum iterations	300
Crossover% rate	0.8
Communication range	R40m
Number of anchor nodes	100
Number of generations	150

6.1. Node Localization Error

In contrast, some range-based localization with a centroid weighted algorithm (LCWA) always finds a solution and does not call for a prior prediction exponent of the route loss. To evaluate the accuracy and location of localized coordinates, DV-HoP procedures are utilized. During routing, the Coefficient for reparation algorithm (CRA) reduces error and corrects the average hop distance between nodes and anchor nodes. DCDA was the most efficient method for node localization. In wireless sensor networks, the average estimate of the position of the sensor node. Serves as essential parameters for evaluating the performance and accuracy of the optimization node's localization algorithm.

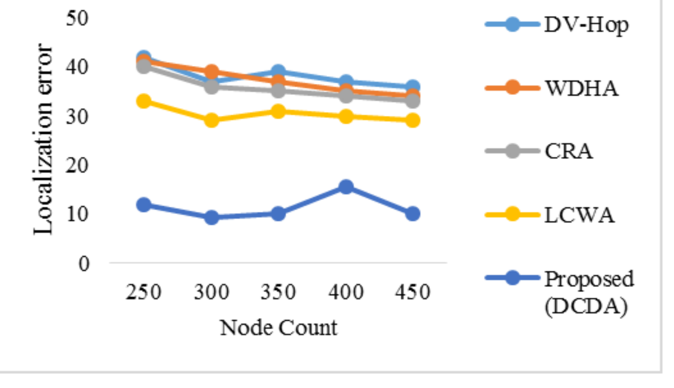

Figure 6 Localization Error vs. Node Count

RESEARCH ARTICLE

The aim of this simulation work was likely to evaluate and compare the performance of the localization algorithm (DEEC-Gauss) as explained in algorithm session 3.2 when using different numbers of sensor nodes, ranging from a small to a large-scale deployment. To perform the simulation. The novel DCDA was subjected to gradient distance, and the nodes were randomly assigned. More than 300 times were spent going through this process. To get the best result. The typical localization error with sensor nodes is shown in Figure 6 for sensor nodes between 200 and 450.

The outcomes are due to the localized sensor node optimization for figuring out the most ideal position of sensors. Demonstrate that the DCDA outperforms the other methods. The localization error results and the overall sensor node count, Table 4, and the results reveal that it outperformed the other four. The performance of the algorithms improves with decreasing localization errors. The correlation analysis is crucial for understanding how the localization algorithm performs in different network scales.

Table 4 Localization Error vs. Node Count

Node Count	DV-HoP	WDHA	CRA	LCWA	Proposed (DCDA)
200	46	42	41	37	11
250	42	41	40	33	11.8
300	37	39	36	29	9.2
350	39	37	35	31	10
400	37	35	34	30	15.5
450	36	34	33	29	10

It provides insights into whether the algorithm can handle larger networks or if its accuracy degrades as the number of nodes increases demonstrate that the proposed DCDA fared better than all current cutting-edge algorithms.

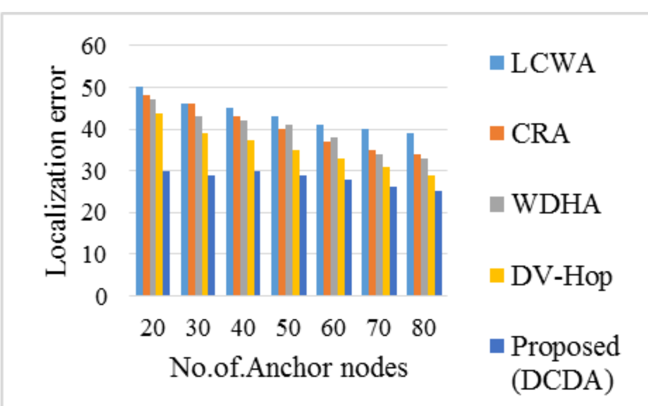

Figure 7 Localization Error vs. Anchor Nodes

The 20-anchor node's actual localized positions are depicted, shown in Figure 7, whose sensor nodes range from 200 to 450. The DCDA was put up against four traditional algorithms in Hence the DCDA significantly improved node localization accuracy by lower the localization error.

The localization error results and the anchor node count are shown in Table 5. It demonstrates that the suggested approach performed better beats all other methods for all nodes between 200 – 450, whereas LCWA, the Coefficient for reparation algorithm (CRA), and DV-Hop have less.

Table 5 Representing Anchor Nodes vs. Localization Error

Anchor Node Count	LCWA	CRA	WDHA	DV-Hop	Proposed DCDA
10	56	54	52	48.3	32
20	50	48	47	43.6	30
30	46	46	43	39	29
40	45	43	42	37.4	30
50	43	40	41	35	29
60	41	37	38	33	28
70	40	35	34	31	26
80	39	34	33	29	25

Thoroughly tested the given technique using the programming language sensor nodes, and 50 gates were used in the experiment, conducted with various nodes distributed over a 2000*2000 square meter region.

6.2. Energy Consumption

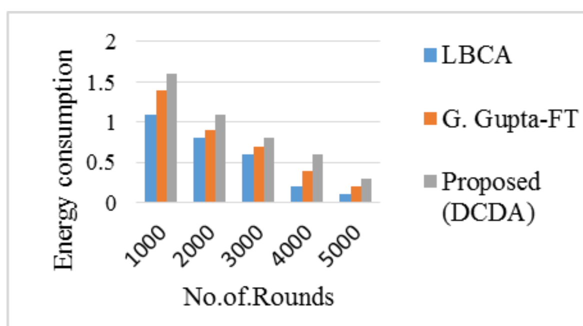

Figure 8 Energy Consumed Scenario 1 (100 Rounds)

The numerical representation of the simulation result for the Energy consumption round is based on Table 6. The initial energy for each sensor node is joules, during the initial power of 10 Joules for all the Gateways. It is considered dead once the node's energy level drops to zero joules. The simulations use the same standard parameters and energy model settings.

Compare the algorithms based on the amount of Energy the Network consumes. The Simulation results for the energy consumed scenario based on rounds are shown in the figure 8. Then, we added the LBCA and G. Gupta FT, DCDA, for the comparison. More sensor nodes are recovered than the competition.

The numerical representation of the simulation result for the Total count of alive Nodes round-based is presented in Table 7.Compare the algorithms based on the amount of Energy the Network consumes.

Table 6 Energy Consumption Round Based

Rounds	Energy Consumption		
	LBCA	G. Gupta-FT	Proposed (DCDA)
500	1.2	1.6	1.8
1000	1.1	1.4	1.6
2000	0.8	0.9	1.1
3000	0.6	0.7	0.8
4000	0.2	0.4	0.6
5000	0.1	0.2	0.3

Table 7 Total Count of Alive Nodes

Rounds	Count of alive Sensor Nodes		
	LBCA	G. Gupta-FT	Proposed (DCDA)
0^{th}	2000	2000	2000
500	320	330	350
1000	280	290	300
2000	200	215	225
3000	145	160	180
4000	120	140	150

6.3. Fault-Tolerant

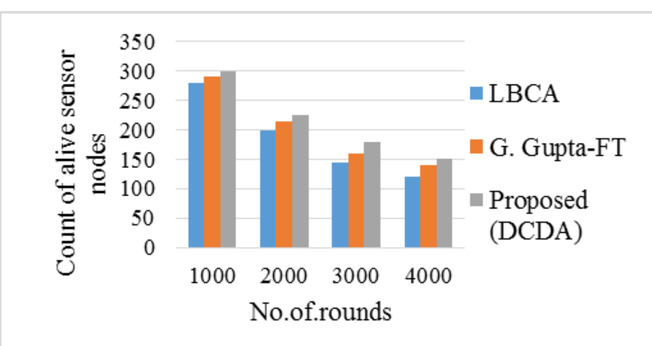

Figure 9 Energy Consumed Scenario 2 (1000 Nodes)

The primary objective of fault tolerance is to ensure uninterrupted operation and uninterrupted delivery of services by a system or process, even in the face of failures or errors. This is of paramount importance in critical systems like computer networks, servers, telecommunications, aerospace systems, financial systems, and safety-critical applications, as it aims to enhance reliability and availability, preventing system crashes or disruptions caused by faults The proposed model, Distributed clustering Distance Algorithm (DCDA), DCDA utilizes a distributed clustering approach, leveraging distance-based techniques to enable precise node localization and facilitate effective data gathering and routing in WSNs as explained in session 3.4. They completed a comparison analysis using contemporary clustering algorithms, which generated performance ratings based on the volume of packets that would reach the Base station and the reduction in error probability and node localization error. Figure 9 shows the simulation results for the energy consumed scenario based on the number of alive node rounds in active voice.

In contrast to contemporary algorithms and conventional methods of localization with centroid weighted algorithm (LCWA), DV-Hop Coefficient for reparation (CRA), and Weighted Distributed Hyperbolic algorithm (WDHA) methods, the new DCDA performance on application demonstrated a reduction in node localization error for minimum 20 to maximum 80 sensor nodes are less than 11% concerning localization error for the node will be decreased for minimum 200 to maximum 450 sensor nodes is 10% to 11%. The DCDA algorithm's performance on more extensive sensor networks will be the focus of subsequent research. Sensor nodes during the stage of cluster development. DCDA uses far more power than the others. Table 8 provides the numerical representation of the simulation results for the Total count of alive sensor Nodes.

Table 8 Total Count of Alive Nodes

Rounds	Count of alive Sensor Nodes		
	LBCA	G. Gupta-FT	Proposed (DCDA)
0^{th}	2000	2000	2000
500	320	330	350
1000	280	290	300
2000	200	215	225
3000	145	160	180
4000	120	140	150

6.4. Gateway

In the context of computer networking, a gateway is a network node or device that serves as an entry or exit point for data traffic between different networks. It acts as an

RESEARCH ARTICLE

intermediary that connects disparate networks, allowing them to communicate and exchange data. Gateways are essential for enabling communication between networks that use different protocols, addressing schemes, or communication technologies. They translate data and protocols from one network to another, ensuring that data can be transmitted and received correctly. The reason for DCDA's superiority lies in its significantly greater capacity to support a more significant number of living sensor nodes, setting it apart from its counterparts. Additionally, the Simulation results for the energy consumed scenario are based on the number of alive gateway rounds, as shown in Figure 10. Table 9 provides the numerical representation of the simulation results for the Total count of alive Gateways round.

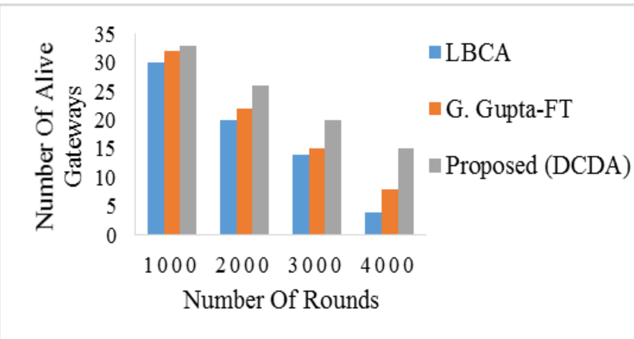

Figure 10 Count of Alive Gateways Based on Rounds

Table 9 Total Count of Alive Gateways

Rounds	Number of alive Gateways		
	LBCA	G. Gupta-FT	Proposed (DCDA)
500	35	35	35
1000	30	32	33
2000	20	22	26
3000	14	15	20
4000	04	08	15

7. CONCLUSION

The technique uses the cluster head's cost function to construct an appropriate one while caring for the exposed sensor nodes in a cluster during the cluster formation phase. DCDA has proposed a distributed method of recovering the flawed cluster members. The proposed technique, which outperforms LBCA, G. Gupta-FT, and the fault-tolerant clustering algorithm, is characterized by the wireless sensor network's 96% active nodes, energy consumption, inactive sensor nodes, and active gateways.

REFERENCES

[1] Wang, L., Er, M.J. and Zhang, S., 2020. A kernel extreme learning machines algorithm for node localization in wireless sensor networks. IEEE Communications Letters, 24(7), pp.1433-1436.2020

[2] Aroba, Oluwasegun Julius, Nalindren Naicker, and Timothy Adeliyi. "An innovative hyperheuristic, Gaussian clustering scheme for energy-efficient optimization in wireless sensor networks." Journal of Sensors 2021 (2021): pp1-12.2021

[3] Zhao, Q., Cheng, Y. and Zhou, T., 2021. Research on Node localization Algorithm in WSN Based on TDOA. In Journal of Physics: Conference Series (Vol. 1757, No. 1, p. 012142). IOP Publishing.2021.

[4] Pandey, O.J., Gautam, V., Jha, S., Shukla, M.K. and Hegde, R.M., 2020. Time synchronized node localization using optimal H-node allocation in a small world WSN. IEEE Communications Letters, 24(11), pp.2579-2583.2020

[5] Farahzadi, H.R., Langarizadeh, M., Mirhosseini, M. and Fatemi Aghda, S.A., 2021. An improved cluster formation process in wireless sensor network to decrease energy consumption. Wireless Networks, 27, pp.1077-1087.2021

[6] Aroba, O.J., Naicker, N., Adeliyi, T. and Ogunsakin, R.E., 2020. Meta-analysis of heuristic approaches for optimizing node localization and energy efficiency in wireless sensor networks. International Journal of Engineering and Advanced Technology (IJEAT), 10(1), pp.73-87.2020.

[7] Huang, X., Han, D., Cui, M., Lin, G. and Yin, X., 2021. Three-dimensional localization algorithm based on improved A* and DV-Hop algorithms in wireless sensor network. Sensors, 21(2), p.448.2021

[8] Rishiwal, V. and Singh, O., 2021. Energy efficient emergency rescue scheme in wireless sensor networks. International Journal of Information Technology, 13, pp.1951-1958.2021

[9] Abdurohman, M., Supriadi, Y. and Fahmi, F.Z., 2020. A modified E-LEACH routing protocol for improving the lifetime of a wireless sensor network. Journal of Information Processing Systems, 16(4), pp.845-858.2020

[10] Ibrahim, B.K., Mahdi, M.A. and Salman, M.A., 2020, April. Triple mobile anchors approach for localization in WSN. In 2020 International Conference on Computer Science and Software Engineering (CSASE) (pp. 174-179). IEEE.2020.

[11] Kumar, S., Kumar, S. and Batra, N., 2021. Optimized distance range free localization algorithm for WSN. Wireless Personal Communications, 117, pp.1879-1907.2020.

[12] Prashar, D. and Jha, N., 2021. Review of secure distributed range-free hop-based localization algorithms in the wireless sensor networks. Multimedia Security: Algorithm Development, Analysis and Applications, pp.283-302.2021.

[13] Cheng, L., Li, Y., Xue, M. and Wang, Y., 2020. An indoor localization algorithm based on modified joint probabilistic data association for wireless sensor network. IEEE Transactions on Industrial Informatics, 17(1), pp.63-72.2020.

[14] D. Prashar, N. Jha, in Three-Dimensional Distance-Error-Correction-Based Hop Localization Algorithm for IoT Devices, 66, CMC-Computer Materials & Continua, 2021, pp. 1529–1549.2020

[15] A. Kaur, N. Agrawal, S. Lal, An accurate localization in wireless sensor networks, in 2020 6th International Conference on Signal Processing and Communication (ICSC) IEEE, 2020, pp. 18–22.2020.

[16] Nagy, J., Oláh, J., Erdei, E., Máté, D. and Popp, J., 2018. The role and impact of Industry 4.0 and the Internet of things on the business strategy of the value chain—the case of Hungary. Sustainability, 10(10), p.3491.2018.

[17] Jaiswal, K.; Anand, V. FAGWO-H: A hybrid method towards fault-tolerant cluster-based routing in a wireless sensor network for IoT applications. J. Supercomputer. 2022, 78, 11195–11227,2022

[18] Dowlatshahi, M.B., Rafsanjani, M.K. and Gupta, B.B., 2021. An energy aware grouping memetic algorithm to schedule the sensing activity in WSNs-based IoT for smart cities. Applied Soft Computing, 108, p.107473.2021.

RESEARCH ARTICLE

[19] Naser Abdali, T.A., Hassan, R., Mohd Aman, A.H., Nguyen, Q.N. and Al-Khaleefa, A.S., 2021. Hyper-angle exploitative searching for enabling multi-objective optimization of fog computing. Sensors, 21(2), p.558.2021.
[20] Idrees, A.K. and Al-Qurabat, A.K.M., 2021. Energy-efficient data transmission and aggregation protocol in periodic sensor networks based fog computing. Journal of Network and Systems Management, 29(1), p.4.2021.
[21] Abdali, T.A.N., Hassan, R., Aman, A.H.M. and Nguyen, Q.N., 2021. Fog computing advancement: Concept, architecture, applications, advantages, and open issues. IEEE Access, 9, pp.75961-75980.2021.
[22] Gao, Y., Xiao, F., Liu, J. and Wang, R., 2018. Distributed soft fault detection for interval type-2 fuzzy-model-based stochastic systems with wireless sensor networks. IEEE Transactions on Industrial Informatics, 15(1), pp.334-347.2019.
[23] Li, L., Dai, H., Chen, G., Zheng, J., Dou, W. and Wu, X., 2019. Radiation constrained fair charging for wireless power transfer. ACM Transactions on Sensor Networks (TOSN), 15(2), pp.1-33.2019.
[24] Hayat, H., Griffiths, T., Brennan, D., Lewis, R.P., Barclay, M., Weirman, C., Philip, B. and Searle, J.R., 2019. The state-of-the-art of sensors and environmental monitoring technologies in buildings. Sensors, 19(17), p.3648.2019.
[25] Abdali, T.A.N., Hassan, R., Muniyandi, R.C., Mohd Aman, A.H., Nguyen, Q.N. and Al-Khaleefa, A.S., 2020. Optimized particle swarm optimization algorithm for the realization of an enhanced energy-aware location-aided routing protocol in manet. Information, 11(11), p.529.2020.
[26] Abdulrab, H., Hussin, F.A., Abd Aziz, A., Awang, A., Ismail, I. and Devan, P.A.M., 2022. Reliable fault tolerant-based multipath routing model for industrial wireless control systems. Applied Sciences, 12(2), p.544.2022.
[27] Biradar, M. and Mathapathi, B., 2021, February. Secure, reliable and energy efficient routing in WSN: A systematic literature survey. In 2021 International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT) (pp. 1-13). IEEE.2021.
[28] Menaria, V.K., Jain, S.C., Raju, N., Kumari, R., Nayyar, A. and Hosain, E., 2020. NLFFT: A novel fault tolerance model using artificial intelligence to improve performance in wireless sensor networks. IEEE Access, 8, pp.149231-149254.2020.
[29] Mostafaei, H. and Menth, M., 2018. Software-defined wireless sensor networks: A survey. Journal of Network and Computer Applications, 119, pp.42-56.2018
[30] Chouikhi, S., El Korbi, I., Ghamri-Doudane, Y. and Saidane, L.A., 2017. Recovery from simultaneous failures in a large scale wireless sensor network. Ad Hoc Networks, 67, pp.68-76.2017.
[31] Mitra, S., & Das, A. Distributed fault-tolerant architecture for wireless sensor network. Informatica, 41(1), 47, 2017.
[32] Singh, S.K., Singh, M.P. and Singh, D.K., 2010. Routing protocols in wireless sensor networks–A survey. International Journal of Computer Science & Engineering Survey (IJCSES), 1(2), pp.63-83.2017.
[33] Aadri, A. and Idrissi, N., 2017. An energy efficient hierarchical routing scheme for wireless sensor networks. Computer science & information technology, pp.137-148.2017.
[34] Moridi, E., Haghparast, M., Hosseinzadeh, M. and Jafarali Jassbi, S., 2020. Novel fault-tolerant clustering-based multipath algorithm (FTCM) for wireless sensor networks. Telecommunication Systems, 74, pp.411-424.2018.
[35] Wang, P. and Tu, G., 2020. Localization algorithm of wireless sensor network based on matrix reconstruction. Computer Communications, 154, pp.216-222.2020.
[36] Li, J., Gao, M., Pan, J.S. and Chu, S.C., 2021. A parallel compact cat swarm optimization and its application in DV-Hop node localization for wireless sensor network. Wireless Networks, 27, pp.2081-2101.2021.
[37] Wang, Y., Yan, Y., Li, Z. and Cheng, L., 2020. A mobile localization method in smart indoor environment using polynomial fitting for wireless sensor network. Journal of Sensors, 2020.
[38] Hao, Z., Dang, J., Yan, Y. and Wang, X., 2021. A node localization algorithm based on Voronoi diagram and support vector machine for wireless sensor networks. International Journal of Distributed Sensor Networks, 17(2), p.1550147721993410.2021.
[39] Khattak, S.B.A., Jia, M., Marey, M., Nasralla, M.M., Guo, Q. and Gu, X., 2022. A novel single anchor localization method for wireless sensors in 5G satellite-terrestrial network. Alexandria Engineering Journal, 61(7), pp.5595-5606.2022.
[40] Agoramoorthy, M. and Praveen Joe, I.R., 2022. Hybrid cuckoo–red deer algorithm for multiobjective localization strategy in wireless sensor network. International Journal of Communication Systems, 35(4), p.e5042.2022.
[41] Vijayan, K. and Raaza, A., 2016. A novel cluster arrangement energy efficient routing protocol for wireless sensor networks. Indian Journal of science and Technology, 9(2), pp.1-9.2016.
[42] Vijayan, K., Ramprabu, G., Samy, S.S. and Rajeswari, M., 2020. Cascading model in underwater wireless sensors using routing policy for state transitions. Microprocessors and Microsystems, 79, p.103298.2020.
[43] Sakthi Shunmuga Sundaram, P. and Vijayan, K., 2022, February. Sleeping Node Scheduling Method Based Redundant Node Energy Reduction in Wireless Sensor Networks. In International Conference on Computing in Engineering & Technology,Singapore: Springer Nature Singapore. (pp. 602-609).2022
[44] Sundaram, P.S.S. and Vijayan, K., 2022. Comparison of the Routing Algorithms Based on Average Location Error and Accuracy in WSN. In Sensing Technology: Proceedings of ICST 2022,Cham: Springer International Publishing.(pp. 411-423).2022.
[45] Sankaran, K.S., Vijayan, K., Yuvaraj, S., Periasamy, J.K., Balasaraswathi, M., Verma, J.P.N. and Tyagi, C.S., 2021. Weighted-based path rediscovery routing algorithm for improving the routing decision in wireless sensor network. Journal of Ambient Intelligence and Humanized Computing, pp.1-9.2021.

Authors

P. Sakthi Shunmuga Sundaram, Full Time Research Scholar, Department of Electronics, and Communication Engineering, College of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, Chennai, Tamil Nadu 603203, India. He completed his bachelor's degree in Electronics & Communication Engineering at Dhanalakshmi College of Engineering, Chennai, under Anna University-2007, and his Master's degree in Applied Electronics at Sri Muthukumaran Institute of Technology (SMIT), Chennai, under Anna University-2011.

K. Vijayan is working as an 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. His research area is 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 and Madras University- 2001. Master's degree in VLSI in Anna University, Chennai, India, June 2003, finished his research and was awarded a doctorate in Electronics & Communication Engineering, VELS University2018.

RESEARCH ARTICLE

How to cite this article:

P. Sakthi Shunmuga Sundaram, K. Vijayan, "Prediction Model to Analyze Source Node Localization Using Machine Learning and Fault-Tolerant in Wireless Sensor Networks", International Journal of Computer Networks and Applications (IJCNA), 10(4), PP: 527-542, 2023, DOI: 10.22247/ijcna/2023/223312.