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Exploring AI and Metaheuristic Optimization in Clustering-Based Localization for WSNs: A Comprehensive Review

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ABSTRACT

Wireless Sensor Networks (WSNs) have become increasingly important in various applications, such as, Internet of Things (IoT), healthcare, target tracking, smart cities, underwater exploration, ecosystem monitoring, and military systems require reliable and accurate localization techniques to enable effective monitoring and data collection, with localization being a critical aspect particularly in large scale deployment. Localization techniques, including range-based methods like Time of Arrival (TOA), Received Signal Strength (RSS), and range-free methods like centroid-based and hop-count-based approaches, aim to accurately determine the targets position. Clustering can improve localization accuracy and energy efficiency. This review explores the integration of Artificial Intelligence (AI) and metaheuristic optimization techniques in clustering-based localization for WSNs. We analyze how AI-driven approaches and metaheuristic algorithms can enhance localization performance, addressing challenges like multipath fading, noise, non-line-of-sight (NLOS) conditions, interference and node mobility. The review identifies opportunities and future research directions, focusing on improving accuracy, reducing energy consumption, and increasing scalability. This study provides insights for researchers and developers working on WSN-based applications, highlighting the potential of AI and metaheuristic optimization in addressing localization challenges.

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INTRODUCTION

Wireless Sensor Networks (WSNs) comprise of numerous small, low-cost sensor nodes distributed across a Region of Interest (ROI) in two- or three-dimensional (2D or 3D) layouts to monitor and report environmental changes, such as weather, ecology, or infrastructure (Capineri & Bulletti, 2021; J. Kumari et al., 2019; Mnasri, 2020; Sayyed & Buss, 2015). These nodes, often deployed randomly or strategically, collect and transmit data aggregation to a Base Station (BS) or sink node, directly or via intermediate nodes, facilitating applications such as environmental monitoring, target tracking, healthcare, smart grids, and surveillance in challenging environments like deep valleys or underwater, where event location is critical (Faheem et al., 2019; Mohsan et al., 2023; Tunca et al., 2014; F. Wang et al., 2011). The dense network of specialized and conventional sensor nodes accurately measures physical variables, with the BS processing collected data to provide valuable insights and support informed decision-making.

Cluster-based structures in localization algorithms is a fundamental network management step that simplifies large-scale sensor deployment by grouping nodes into clusters (Afsar & Tayarani-N, 2014; Sambo et al., 2019). Typically based on distance or signal strength metrics, residual energy, or neighborhood relationships (inter or intra) to enhance energy efficiency and accuracy in WSNs by enabling distributed and parallel processing through Cluster Heads (CHs) (Ahmed

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et al., 2024; Rostami et al., 2018; Shahraki et al., 2021). CHs coordinate local information aggregation and assist in localization by forming local coordinate systems, often using triangulation or distance estimation techniques (Sucasas et al., 2016). This approach reduces communication overhead, computational complexity, and facilitates efficient management of node location changes within clusters, ultimately improving scalability and network performance (Shahraki et al., 2021). Figure 1 illustrates this WSN architecture.

WSNs are integral to computing paradigms like Internet of Things (IoT) and cloud computing. A notable localization technology, LoRa, (Long Range) utilizes Received Signal Strength (RSS) measurements for outdoor target localization, particularly in smart cities (Bonafini et al., 2019; Lam et al., 2019). However, WSNs face challenges such as energy consumption, data routing, coverage, and node localization. LoRa's low power consumption and limited bandwidth make it suitable for IoT localization (Li et al., 2011). Also, in areas without existing infrastructure, GPS-based positioning can be difficult for sensors, highlighting the need for alternative localization solutions.

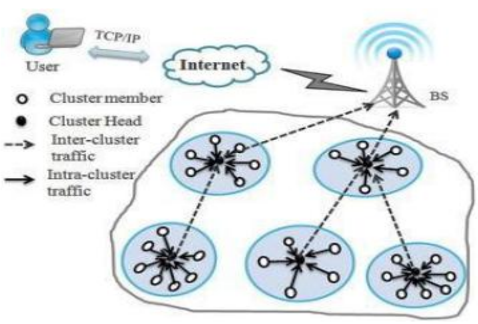

Figure 1. Clustering architecture in a WSN

Localization algorithms often rely on GPS anchor nodes for precise location determination. While GPS provides high precision, its cost and energy demands make it impractical for large-scale WSNs. Simulations are often employed to develop and test localization algorithms due to the challenges of real-world GPS deployment (Lu et al., 2022). Energy efficiency remains a critical concern, driving innovations in low-power protocols like Two-Way Ranging (TWR) and beacon-based systems.

Localization Approach

Localization in WSNs involves determining node positions through various methodologies tailored to resource constraints and deployment scenarios. These approaches are broadly categorized based on their architectural and operational frameworks as shown in Fig. 2.

Centralized vs. Distributed

Centralized approaches rely on a central node (e.g., a base station) to compute positions using aggregated network data, minimizing computational load on individual nodes but introducing single-point failures and communication bottlenecks (Xia et al., 2017).

Distributed methods enable nodes to self-localize using neighbor data, enhancing scalability and fault tolerance at the cost of increased node-level computation (Sun et al., 2012).

Anchor-Based vs. Anchor-Free

Anchor-based techniques depend on nodes with known positions (via GPS or manual deployment) as reference points. These anchor nodes help localize unknown nodes through trilateration or multilateration, with accuracy improving with higher anchor density (G. Han et al., 2016; P. Singh et al., 2018; Xia et al., 2017).

Anchor-free algorithms estimate relative positions using network connectivity and topological relationships, eliminating hardware costs but requiring complex coordination (G. Han et al., 2016; Paul & Sato, 2017; Zaarour et al., 2024).

Range-Based vs. Range-Free

Range-based algorithms measure physical distances or angles between nodes using techniques like Angle of Arrival (AoA), Received Signal Strength Indicator (RSSI), Time of Arrival (TOA), or Time Difference of Arrival (TDOA). These methods offer higher accuracy but are sensitive to environmental interference and require additional hardware (Sivasakthiselvan & Nagarajan, 2020).

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Range-free approaches use connectivity metrics (e.g., hop counts) or proximity data to estimate positions. Examples include the Centroid, Distance Vector (DV)-Hop, and Amorphous algorithms, which trade precision for lower energy consumption and cost. Hybrid range-free methods, such as APIT and SANLA, combine connectivity with geometric tests to improve accuracy (Sivasakthiselvan & Nagarajan, 2020).

Location estimation algorithms are crucial for determining the geographical location of sensor nodes, helping identify the origin of events. Numerous algorithms, utilizing different principles and technologies, have been introduced in the literature. Most research emphasizes approaches where the locations of certain nodes are known in advance, and these known positions serve as references for estimating the locations of other nodes in the network. Proximity-based localization involves forming clusters with GPS-enabled cluster heads, which use their positions to estimate the locations of other nodes within the cluster.

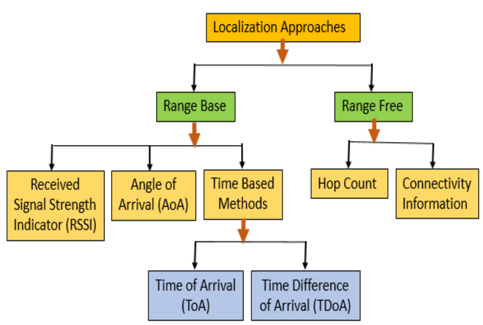

Figure 2. Localization Approaches

Clustering Optimization Process

Optimizing the clustering process in WSNs involves addressing key issues in Cluster Head (CH) selection, data aggregation, cluster formation, and data communication as shown in Figure 3. This includes determining the optimal number of clusters, cluster density, and balance among clusters, as well as finding the right cluster size and level of inter-cluster communication to maximize data aggregation, and communication efficiency (Bongale et al., 2022).

Cluster head selection is a crucial step in most clustering protocols for WSNs, as CHs act as gateways between SNs and the BS. Effective CH selection improves energy efficiency and network lifespan. Techniques for optimizing CH selection are generally divided into self-organized (distributed control) and supported (centralized control) schemes (Y. Han et al., 2018; Salehi et al., 2022; Zhang et al., 2013). In self-organized schemes, each sensor node independently runs its algorithm to decide whether it should become a CH, thereby enabling decentralized decision-making and adaptability within the network

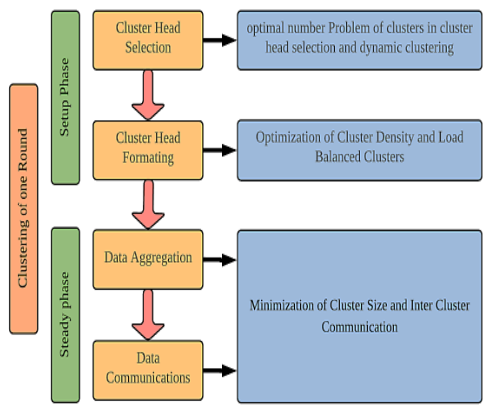

Figure 3. Clustering optimization methods in a WSN.

Clustering objectives

Clustering in WSNs is designed to meet the diverse requirements of various applications by focusing on several key objectives. These include data aggregation to efficiently combine sensor data, load balancing to evenly distribute network tasks, fault tolerance to maintain operation despite node failures, and extending network lifetime through energy-efficient practices (Begum & Nandury, 2022; Darabkh & Al-Akhras, 2025; Sreenivasamurthy & Obraczka, 2024). Additionally, clustering aims to enhance scalability for large networks, improve reliability and quality of service (QoS) support, and ensure security within the network, which guide the design of clustering algorithms (Sivasakthiselvan & Nagarajan, 2020; Jubair et al., 2022). Each of these goals plays a vital role in optimizing the

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overall performance and robustness of wireless sensor networks.

Performance parameters

This section discusses evaluation criteria for localization algorithms, highlighting the importance of comparing performance metrics to assess their effectiveness. Evaluating localization algorithms helps determine their suitability for specific applications and compare them to existing state-of-the-art methods (Paul & Sato, 2017). This review concentrates on the key outcomes and factors influencing localization:

Accuracy:

In localization refers to how closely estimated node positions match actual positions. It's often measured using root mean square error (RMSE) or absolute mean square error, calculated as the difference between estimated and actual coordinates which is given by eq. (1). Here (x_i, y_i) are the expected coordinates and the $(\hat{x}_i, \hat{y}_i)$ are the estimated coordinates. Clustering nodes can improve location management by allowing CH to track changes within their clusters.

$$E_{rms} = \sqrt{(x_i - \hat{x}_i)^3 + (y_i - \hat{y}_i)^2} \quad (1)$$

The average root mean square of the complete network can be calculated as follows;

$$AvgE_{rms} = \frac{\sum_{i=1}^{n} \sqrt{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2}}{n} \quad (2)$$

Network topology:

Clustering enables efficient location management, as CHs track node positions and energy levels within their clusters. This facilitates instant reporting of node deaths or movements. Node deployment topology, whether grid or random, significantly impacts localization technique performance, making it essential to consider topology in simulations for evaluating and comparing the effectiveness of different localization algorithms.

$$C_n = \frac{N(N-1)}{2} \quad (3)$$

where C_n is the number of connections required for communication and N is the number of sensor nodes.

Coverage:

Coverage and connectivity in WSNs are essential for ensuring that a sufficient number of nodes are deployed to effectively monitor a target area and maintain communication with the base station, regardless of the exact positional accuracy of the nodes. The ability of a localization technique to identify all nodes in the network depends on factors such as node density and the placement of beacon or anchor nodes. The spatial arrangement of anchor nodes can significantly influence the accuracy of position estimation. To model and analyze network coverage, the probability density function of a normal distribution is often employed, providing a statistical framework for evaluating how well the deployed sensors observe the region of interest. Certain localization methods may not successfully determine the positions of every node, especially as network density and anchor placement vary, highlighting the importance of careful deployment planning and coverage modeling.

$$\emptyset(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \quad (4)$$

Cost:

The cost of localization in Wireless Sensor Networks (WSNs) is evaluated based on factors like energy consumption, communication overhead, setup requirements, and localization time. Due to the need for advanced computational and communication capabilities, localization often demands higher costs and power consumption. Given the hardware costs and size limitations, relying on GPS is not feasible. To maximize network lifetime, cost-effective algorithms are beneficial, but there's a trade-off between cost and accuracy, influenced by application-specific

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criteria. The total cost can be estimated using a specific formula, such as Eq. (5).

$$Cost_{Total} = \sum_{i=1}^{n} CS_i + \sum_{i=1}^{n} PCS_i + \sum_{i=1}^{n}(\prod_{i=1}^{n}(CO, S_i)) + SDC \quad (5)$$

The total cost includes CS_i: Cost of each sensor node, PCS_i: Power consumption cost of each sensor nodeCO: Communication cost per sensor node, SDC: Deployment cost of sensor nodes. These factors contribute to the overall cost estimation.

CLUSTERING FOR LOCALIZATION

Clustering is an effective node localization technique in WSNs that improves accuracy by limiting the localization area and creates a structured framework for easier location extraction. This approach is beneficial even in irregular or random deployments, and studies have shown that clustering-based methods achieve lower localization errors and better energy efficiency compared to non-clustered approaches.

Review on Clustering

This section reviews various clustering approaches and optimization techniques, focusing on cluster formation and routing, energy optimization, and QoS. It highlights the need to balance competing factors like network lifetime, coverage, scalability, reliability, and throughput. The review specifically explores AI-based and meta-heuristic optimization methods, including bio-inspired, Swarm Intelligent (SI), fuzzy logic (FL) and learning techniques, designed to minimize energy consumption, extend both network lifetime and connectivity.

The author in (Kumar & Agrawal, 2022) suggests combining clustering techniques with meta-heuristics, such as Genetic Algorithm (GA), to optimize energy usage in WSNs. This approach leverages the strengths of both methods to find optimal solutions, with GA being a popular choice for routing and clustering in WSNs. GA is used to extend the lifetime of CHs, improving network life (Sahoo et al., 2022) and service efficiency (A. M. Jubair et al., 2021). GATERP algorithm in Ref. (Mittal et al., 2019), utilizes GA-based threshold-sensitive energy-efficient routing protocol (TERP) to optimize CH selection based on cohesion and cluster division. It streamlines inter-cluster communication and balances load through multi-hop routing, minimizing energy consumption and extending network lifetime, outperforming traditional methods. Similarly, Adaptive GA (AGA) based routing protocol calculate fitness values based on factors like residual energy, inter and intra-cluster distance to evaluate the suitability of nodes as CHs to optimize network performance (Sahoo et al., 2022),(S. He et al., 2024).. The algorithm optimizes energy usage but has slow convergence due to chromosome length equaling the number of nodes and doesn't address potential disruptions during CH changes.

The Artificial Bee Colony (ABC) algorithm improves CH efficiency by computing multi-objective fitness values,(Luo et al., 2017). Ref. (A. Singh et al., 2019) described a hybrid approach combining GA and binary Ant Colony Optimization (ACO) was used to achieve optimal coverage, reduce data redundancy, and minimize the number of sensors required. Additionally, a two-stage bio-inspired approach using GA and Artificial Bee Colony Optimization (ABCO) ensures reliability by improving clustering and finding optimal routes between nodes (Ezugwu et al., 2021),(Yue et al., 2023). The GA and Particle Swarm optimization (PSO) technique optimizes clustering and routing (Anand & Pandey, 2020), enhance network lifetime by selecting the best CH based on node proximity and energy level parameters, prioritizing energy-efficient paths for data transmission to the BS and improve scalability. The DESA protocol in (Potthuri et al., 2018) combines Differential Evolution and Simulated Annealing to optimize Cluster Head selection in WSNs, aimed to avert premature failure of CHs to attain an extending network lifetime through a four-phase process and hybrid mutation strategy, outperforming LEACH, HSA, MHSA, and DE protocols in terms of network lifetime and energy efficiency.

The fuzzy logic-based algorithm found an optimal performance for both clustering and multi-hop routing processes [40], with reduced

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overhead energy efficiency for cluster formation [41], Authors in (Gajjar et al., 2016) introduced FAMACROW, a cross-layer protocol that integrates fuzzy logic, ant colony optimization (ACO), and MAC layer strategies for unequal clustering and routing in WSNs. It operates in three phases, using fuzzy logic to select cluster heads based on residual energy, link quality, and neighboring nodes as input parameters. The protocol forms smaller clusters near the BS to mitigate energy holes and enhance reliability. In (Jagannathan et al., 2021) a Collision-Aware Routing using Multi-Objective SOA (CAR-MOSOA) is proposed to efficiently transmit alert messages in IoT-enabled WSNs. The approach focuses on energy conservation, lifetime enhancement, QoS, and security. Simulation results show that CAR-MOSOA outperforms existing methods, reducing energy consumption and delay by 25% and 34%, respectively, while increasing network lifetime and packet delivery ratio.

Yuebo et al. (2023) Proposes NFCRP, a novel fuzzy clustering and routing protocol using improved Particle Swarm Optimization (PSO) to tune fuzzy rules. NFCRP optimizes clustering and routing, reducing energy consumption and improving network lifetime. Simulation results show NFCRP outperforms LEACH, EEFUC, EFUCA, FBCR, and FMSFLA in network lifetime (up to 79.59% increase), traffic load balancing, network throughput (up to 71.79% improvement), and energy efficiency (up to 53.95% reduction).

This study of (Rami Reddy et al., 2023) proposed an energy-efficient cluster head selection protocol, EECHIGWO, using an improved Grey Wolf Optimizer (GWO) algorithm. The protocol considers factors like sink distance, residual energy, and intra-cluster distance to select CHs, and features multi-hop communication. It optimizes fitness function values to extend WSN lifetime, balances energy consumption, and avoids premature node deaths, resulting in improved network stability, throughput, and lifetime. In (Debasis et al., 2023) EECA model uses Artificial Neural Network (ANN) to select CHs based on residual energy, event detection, distance to base station, and neighbor count. CHs are chosen from nodes with sufficient energy, and a maximum cluster size limit prevents large clusters.

The model reduces redundant data transmission and idle listening, resulting in significant energy savings compared to existing MAC protocols. Ref in (Soni & Shrivastava, 2018) proposed two reinforcement learning-based algorithms, RLBCA and ODMST, to address the hot-spot problem in WSNs. RLBCA forms CHs, while ODMST uses a mobile sink to collect data, reducing energy consumption. However, these approaches are limited to small-scale, static, and homogeneous networks, restricting their scalability and adaptability.

Clustering Algorithms for Localization in WSN

In this section, we present different clustering algorithms for localization in WSN. Localization algorithms in WSNs estimate the positions of unknown sensor nodes using a few nodes with known locations (anchor or beacon nodes). This technique reduces energy consumption by clustering un-localized nodes and having cluster heads perform localization tasks, enabling applications like smart devices, cellular networks, robotics, and underwater sensor networks.

The work in (Chang et al., 2018) proposed a cluster analysis-based localization technique using mobile anchor nodes with directional antennas to improve localization accuracy. The directional antennas radiate energy in a specific direction, reducing interference and increasing accuracy. Sensor nodes receive beacon messages from the anchor nodes, which are used to estimate their location. The technique uses the Sum of Squared Error (SSE) to measure cluster scatter and selects the centroid as the approximate sensor node location. Likewise, a tennis assistant referee system leveraging intelligent sensor networks and data understanding (Liu, 2021), uses multi-granularity features to enhance tracking accuracy and has proven efficiency and superior QoS performance compared to state-of-the-art systems.

Ref.(Sabale & Mini, 2019), focused on clustering approach using the D-connect

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technique to optimize anchor node path planning in WSN localization, addresses the issue of collinear beacon nodes and reducing localization time and error. Another approach (Bala Subramanian et al., 2021) introduced a technique using two anchor nodes with Z-curve trajectories for bidirectional localization and data transmission, ensuring accurate localization of static nodes in the sensing field by guiding anchor nodes along a path that covers the entire area.

In (Hosseini & Mirvaziri, 2020) a clustering-based target tracking strategy in WSNs is proposed, aims to achieve minimal energy consumption and the lowest possible tracking error by leveraging the inherent WSN characteristics in its clustering design. The K-means algorithm is used for clustering, and nodes are arranged in concentric circular layers for flexible routing and balanced energy use by ensuring that the data transfer distance is distributed more evenly among nodes. This approach ensures that clusters are efficiently formed and maintained, supporting WSN accuracy and energy-efficient target tracking.

Author in (Wajgi, 2024) presented an energy-efficient clustering-based localization algorithm for WSNs that balances accuracy with low computational complexity. Sensor nodes are grouped into clusters based on received signal strength (RSS) at anchor nodes, which act as cluster heads. By combining distance calculations with AoA data, the algorithm estimates node locations and forms local maps, enhancing localization accuracy. A density control strategy during cluster formation minimizes energy consumption by reducing communication overhead. Compared to adaptive clustering and improved K-means algorithms, the proposed method achieves superior performance in terms of average energy consumption and WSNs.

The study in (Sahana & Singh, 2020) developed a cluster-based localization technique for underwater environments enhances energy efficiency and network longevity through dynamic clustering with rotating roles. High-energy nodes serve as cluster heads, while low-energy nodes act as members. Cluster head selection is based on factors like distance from the base station and node density to minimize intra-cluster communication. A backup node is designated to ensure continuity in case of cluster head failures, chosen for its proximity and strong link quality. Anchor nodes with predefined locations enable accurate positioning of cluster heads and members, reducing localization errors and effectively balancing energy use across the network. This approach prevents hot-spot issues and adapts to dynamic network conditions.

An energy-aware unequal clustering method tackles the energy hole issue in multi-hop WSNs using heterogeneous nodes with different energy levels (Gupta & Pandey, 2016). The base station’s location is known and distant from the network. CHs are chosen based on neighboring nodes, and the relay selection considers energy consumption, not just distance. Data transmission is organized into major and mini slots to extend each round, while stable clusters over multiple rounds reduce overhead. Nodes estimate their distance to the BS via signal strength, and cluster setup and data aggregation happen every round, improving energy balance and network lifetime by integrating energy-aware metrics and minimizing communication overhead.

In (Purusothaman & Gunasekaran, 2021), an intelligent localization model for WSNs called Rooster Updated Attacker-based Rider Optimization Algorithm (RUA-ROA) is developed, a hybrid algorithm combining ROA with Chicken Swarm Optimization (CSO). It determines optimal anchor node locations and then locates rest nodes using same algorithm. RUA-ROA aims to improve node localization accuracy in WSNs by checking node movement direction for precise localization. The algorithm leverages ROA's strengths and another optimization method to optimize anchor node placement towards target nodes. Weights are determined for each anchor node based on RSS, enhancing network localization performance and optimizing node locations effectively.

The TDSDV-Hop algorithm in (X. Wang et al., 2023) improves upon traditional DV-Hop by applying topological structure similarity to correct hop counts. This similarity measure converts discrete hop counts to precise continuous values, enhancing accuracy. A hop-correction equation is

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established, and optimal parameters are simulated to obtain accurate hop counts. Unknown node coordinates are calculated using the least square method and optimized with the levy adaptive improved bird swarm algorithm (LSABSA). Simulation results show TDSDV-Hop outperforms other algorithms in localization accuracy, low latency, and communication cost.

Ref (Cherntanomwong & Sooraksa, 2018) presented Fingerprint-based localization technique that uses soft-clustering to handle signal fluctuations, comparing signal characteristics RSSI to a database of known parameters. Fuzzy C-Means clustering reduces computation time and database size by grouping related data. This approach enables faster target location estimation by calculating the location within a limited cluster of fingerprints, rather than searching the entire database. By leveraging clustering, the system achieves improved accuracy and efficiency, making it suitable for applications requiring precise location estimation. The use of reference nodes further enhances location estimation, allowing for more reliable and accurate results.

In (Robinson et al., 2022) a 3D manifold and machine learning (ML) clustering-based localization algorithm is developed to improve accuracy in WSNs. This technique identifies faulty nodes, measures error using Root Mean Square Error (RMSE), and extracts reliable data, resulting in reduced transmission errors and increases localization accuracy by detecting unknown nodes. While authors of (S. Kumari et al., 2022) aims to ensure accurate location prediction using MLAELD, a machine learning architecture that utilizes Bluetooth Low Energy (BLE) beacons to track excavator locations. The system collects signal strength data from multiple beacons and trains regression models (linear regression, K-nearest neighbor, decision tree, and random forest) to predict the real-time locations of persons and machines with high precision.

Another approach (Yan et al., 2018) proposes a kernel-based learning algorithm for indoor localization using RSSI fingerprints. The algorithm involves offline training with ISODATA, an iterative self-organizing data analysis techniques algorithm pre-processing and c-support vector classification for measurement-label classification. Regression learning with hybrid kernel and cross-validation techniques is applied to each measurement-position subset. Online, the classification result determines the regression function for target position estimation. Field tests demonstrate improved positioning accuracy without added computational complexity.

The work in (Sekhar et al., 2021) developed a metaheuristic-based Group Teaching Optimization Algorithm with Node Localization (GTOA-NL) for WSNs, which uses anchor nodes to determine unknown node positions in an iterative way with reduced localization error and maximum accuracy. Euclidean distance is used to calculate node distance and derive the fitness function for indoor environments. A Grey Wolf Ant Lion Recurrent (GWALR) localization method is put into operation in (Sruthi & Sahadevaiah, 2022) to minimize path loss and localization error in WSNs. GWALR uses improved RSSI to track sensor node locations and applies Ant Lion optimization to the Grey Wolf model to set thresholds, with anchor nodes detecting unknown nodes. Both approaches aim to improve accuracy and throughput while minimizing localization errors.

Ref (Rama & Murugan, 2020) developed a WSN localization technique using Firefly Algorithm (FA) based Artificial Neural Network (ANN) to track mobile nodes. FA improves ANN accuracy, estimating node positions using RSSI fingerprint values and optimized using Principal Component Analysis (PCA) to reduce data size. Affinity Propagation Clustering (APC) is applied to minimize position error and enhance location prediction. The trained FA-ANN model achieves 95% localization accuracy and minimizing error and energy consumption with improves node prediction rate.

A Particle Filter (PF) combined with Support Vector Machine (SVM) for energy-efficient target tracking in WSNs is presented in (Reddy Madhavi et al., 2023). This approach leverages the strengths of PF in tracking and localization, along with SVM's machine learning

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capabilities, to achieve accurate target location determination while minimizing energy consumption. Another approach in (Khedr et al., 2023) discuses Energy-Aware Radial Clustering-based Optimized Deep Convoluted Learning (EARC-ODCL) algorithm for congestion-aware continuous target tracking and boundary detection. EARC-ODCL uses a multi-objective golden eagle optimization to select optimal cluster heads and a deep convoluted neural network to identify sensor node boundaries. A piecewise linear regression approach predicts network congestion, minimizing data loss. Simulations show EARC-ODCL achieves higher accuracy in target tracking and boundary detection, with reduced data loss performance metrics.

The study in (P. Singh et al., 2021) proposed a location optimization approach for dynamic WSNs using the Naked-Mole-Rat Algorithm (NMRA). Their method enables 2D localization by employing a single static anchor node and a dynamic virtual anchor, using a hexagonal projection model to pinpoint moving target nodes. NMRA is used to optimize target node positions, achieving minimized localization errors (down to 0.21) and fast convergence (0.1834 s), with results validated against algorithms like PSO and FA. In another study (S. Singh et al., 2024), the authors propose a hybrid algorithm, TSNMRA, which combines tunicate swarm and naked mole-rat optimization, to dynamically localize target nodes in a network. This approach uses a single static anchor node and virtual anchors with a hexagonal projection method to determine node locations. The effectiveness of TSNMRA is evaluated by comparing it to other optimization strategies, focusing on localization accuracy and the number of nodes successfully localized.

Table 1: Analysis of existing learning methods in WSN localization

Ref no / Author	**Localization Algorithm**	**Technique**	**Objective**	**Advantage**	**Limitations**	**Performance**	**Simulation Tool**
Chang et al., 2018	K-Means algorithm for clustering	DPE approach based AoA and ToA	Cluster analysis method (SSE) for localization	eliminates interference and increase the accuracy of localization	requires priori information and is limited to static node	Throughput, Access delay & energy	IRIS mote platform
Sabale & Mini, 2019	D-connect	Hop Count	Optimizing path planning and reduced delay	minimize localization error	energy level and minimum SNR are considered for clustering	Trajectory length decrease by 380m, and reliability estimation	Matlab
Hosseini & Mirvaziri, 2020	KNN clustering and fuzzy deduction	Layer count	Timely target tracking	minimizes tracking errors	energy consumption	Energy efficiency and network lifetime	Matlab
Wajgi, 2024	K-means algorithm	AoA and RSSI	Reduce energy dissipation & precision	minimizing clustering overhead & optimization complexity	Static cluster assumption	Average energy consumption and network longevity	Matlab

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Ref no / Author	Localization Algorithm	Technique	Objective	Advantage	Limitations	Performance	Simulation Tool
(Sahana & Singh, 2020)	Backup node	Satellite via GPS	Well localized sensor nodes	Enable underwater dynamic clustering	Potential data loss or delay	Lifetime and accuracy	NS-2
Gupta & Pandey, 2016	EADUC protocol	Range free	Enhance energy efficiency	Balanced energy consumption among cluster head	Scalability challenge	Network lifespan	Matlab
(Purusothaman & Gunasekaran, 2021	Hybrid RUA-ROA	RSSI and RSS threshold	Able anchor node location	Reduce errors and improve accuracy	Computational complexity	convergence and statistical analysis	NS-3
X. Wang et al., 2023	Layered clustering with K-means	DV-Hop count	Re-clustering iteration for target tracking	Mini-energy consumption and least tracking error	energy level & mini-SNR consideration for clustering	energy efficiency and reliability estimation	Matlab
Cherntanomwong & Sooraksa, 2018	Fuzzy-C-Means (FCM) for clustering	Range based using RSSI data	Fingerprint based localization	Handle signal fluctuations	Upkeep in dynamic environments	Accuracy and time complexity	Matlab
Robinson et al., 2022	MLAELD based clustering	RSS data from BLE beacons	extract reliable data for faulty nodes	extracting reliable data for high location perdition	complexity or quality of training data	Accuracy, energy consumption and cost	Matlab
(Yan et al., 2018	ISODATA by C-SVC	Hybrid kernel based RSSI	develop an indoor localization algorithm	Low computational complexity	depends on quality of training data	accuracy and time complexity	field test
Rama & Murugan, 2020	GTOA-NL	Range based Euclidean distance	Improve indoor location algorithm	suitable for indoor environments	complexity in parameter tuning	Transmission range, ranging error and no. of anchor nodes	Matlab

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Ref no / Author	Localization Algorithm	Technique	Objective	Advantage	Limitations	Performance	Simulation Tool
(Reddy Madhavi et al., 2023	Hybrid of FA -ANN based clustering	RRSI fingerprint	regulate accurate position of mobile nodes	High localization accuracy (95%)	Complex algorithm and environmental factors	Accuracy, location time and average energy consumption	Train test
Sekhar et al., 2021	Particles Filtering	PF-SVM classifier	maximize distance between the two classes	minimizing clustering overhead nearly 49%	Potential complexity of the PF with SVM	Energy efficiency and network lifetime	Matlab
P. Singh et al., 2021	NMRA optimized coordinates	hexagonal projection technique	minimize error and maximize location accuracy	Ability to handle dynamic target nodes in 2D scenarios	technique initial coordinate estimation accuracy	Time convergence	Monte Carlos
S. Singh et al., 2024	TSNMRA-based clustering	RSSI and AoA	acquire 2D coordinates of target nodes	accurate localization in dynamic environments	Dependency on the single static anchor node accuracy.	Accuracy and no. of nodes localized	Matlab

FUTURE CHALLENGES, OPEN ISSUES AND ITS SOLUTIONS

Localization is crucial for event origin tracking in WSNs. Despite advancements in clustering-based localization, challenges persist, affecting accuracy, energy efficiency, scalability, and robustness. Overcoming these challenges is essential to enhance network performance and prolong sensor lifetimes.

Key Potential and Challenges/Open Issues

Localization Accuracy

1. Clustering improves localization accuracy by strategically using anchor nodes and localizing nodes within clusters, due to reduced distance estimation errors.
2. Irreplaceable nodes can lead to increased energy consumption and deviations in unlocalized nodes.
3. Environmental factors like signal interference, multipath effects, and NLOS conditions reduce localization accuracy.
4. Dynamic node movements and changing network topologies complicate position estimation within clusters.
5. Existing algorithms often struggle to maintain high accuracy in these scenarios.
6. There exists a need to develop a more efficient localization technique to achieve higher accuracy.

Energy Consumption and Network Life-Time

1. Optimized resource allocation and reduced energy consumption can increase the lifetime of WSNs.
2. Excessive communication during localization and clustering drains energy and causes latency in WSNs
3. Limited energy resources and need for energy efficiency.

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4. High localization accuracy and energy conservation often conflict, and finding the right balance through adaptive algorithms is still an unresolved issue.

Scalability and Network Management

1. Effective handling large-scale networks with numerous nodes and complex topologies.
2. Clustering enhances large-scale networks by streamlining topology, cutting communication overhead, and facilitating hierarchical data aggregation, ultimately boosting bandwidth efficiency and network performance.
3. Balancing anchor count, placement, and energy efficiency remains complex, especially in large-scale or mobile networks.
4. Large-scale or mobile WSNs struggle with maintaining stable clusters and efficient localization due to complexity and overhead issues, impacting real-time functionality.

Robustness

1. Clustering outperforms methods like DV-Hop in NLOS or obstructed environments by creating structured meshes around obstacles
2. Increased resilience to node failures and environmental changes.
3. Suitable for various domains (e.g., IoT, WSNs, robotics).
4. Developing efficient, scalable, and adaptive clustering algorithms.
5. Sparse anchor deployment risks large residence areas and higher positioning errors
6. Vulnerability to attacks and need for secure localization.

Optimization of Nodes and Time Convergence

1. Node optimization means improving the node's response time.
2. AI and meta-heuristic algorithms have shown promise in improving localization and clustering.
3. Increasing the number of anchor nodes can lead to longer optimization times for the node.
4. Challenges remain in adapting these methods for real-time, resource-constrained WSN environments.
5. Ensuring robustness and low computational cost is critical.

Emerging Solutions and Research Directions.

1. Advanced algorithms: Developing hierarchical clustering schemes that break large networks into smaller sub-clusters, enhancing scalability and minimizing latency.
2. Hybrid approaches: Merging range-based and range-free methods with clustering enhances localization accuracy while balancing energy use. Adding machine learning models to dynamically correct errors in changing environments shows promise techniques.
3. AI and Meta-Heuristics Integration: Leveraging bio-inspired algorithms (e.g., Genetic Algorithms, Particle Swarm Optimization) and machine learning can boost cluster formation and localization performance. However, they need to be optimized for lower computational complexity and energy consumption. for improved accuracy, efficiency, and adaptability.
4. Energy-Aware and Unequal Clustering: Designing clustering protocols that account for node energy differences and use varying cluster sizes based on distance to the base station can balance energy use and prolong network lifespan.
5. Robust Network Approach: Future algorithms need to include mobility-aware features to ensure localization accuracy and cluster stability in dynamic settings.

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6. Secure Localization Protocols: Designing secure clustering-based localization techniques for node authentication and encryption to address threats such as eavesdropping, node compromise, Sybil, sinkhole, and denial-of-service (DoS) attacks.

CONCLUSION

This paper presents a thorough examination of clustering-based localization in Wireless Sensor Networks (WSNs), focusing on the fusion of Artificial Intelligence (AI) and metaheuristic optimization techniques. We explore key localization aspects in large-scale deployments, clustering strategies, and intelligent optimization algorithms like Genetic Algorithms, Particle Swarm Optimization, and machine learning-driven techniques. Clustering algorithms improve localization accuracy by dividing the network into smaller subgroups, minimizing sensor node communication overhead, and reducing computational complexity while meeting quality of service requirements.

Our analysis reveals that these hybrid approaches significantly improve localization accuracy, energy efficiency, and scalability, leveraging learning platforms for optimized solutions. We discuss various AI-driven and metaheuristic-based methods, highlighting their potential for large-scale and dynamic WSN deployments. The paper highlights potential applications in emerging technologies and identifies ongoing challenges, emphasizing the need for further research to develop more effective and practical localization solutions for WSNs.

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