IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 27 February 2024, accepted 2 April 2024, date of publication 5 April 2024, date of current version 15 April 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3385487

SURVEY

Optimization Algorithms for Wireless Sensor Networks Node Localization: An Overview

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ABSTRACT Wireless Sensor Networks (WSNs) play a critical role in numerous applications, and accurate localization of sensor nodes is vital for their effective operation. In recent years, optimization algorithms have garnered significant attention as a means of enhancing the WSN node localization. This paper presents an in-depth exploration of the necessity of localization in WSN nodes, and offers a comprehensive review of the optimization algorithms used for this purpose. This review encompasses a diverse range of optimization techniques, including evolutionary algorithms, swarm intelligence, and metaheuristic approaches. Key factors such as localization accuracy, scalability, computational complexity, and robustness were systematically evaluated and compared across various optimization algorithms. Additionally, the study sheds light on the strengths and limitations of each optimization approach and discusses their applicability in different WSN deployment scenarios. The insights provided in this review serve as valuable resources for researchers and practitioners seeking to optimize WSN node localization, thus promoting the efficient and reliable operation of WSNs in diverse real-world applications.

INDEX TERMS Wireless sensor networks, WSNs-6LoWPAN, localization, optimization algorithms, 2D, 3D, irregular surfaces.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) have become increasingly prevalent in diverse applications, such as environmental monitoring [1], healthcare [2], agriculture [3], and infrastructure management [4]. In WSNs, the accurate localization of sensor nodes is crucial for ensuring effective operation and enabling location-based services [5]. This enables asset tracking, disaster management, precision agriculture, and other services that rely on precise spatial information [6].

Localization involves estimating the geographical coordinates or relative positions of sensor nodes within the network [7]. Accurate WSN node localization offers numerous benefits and enables a wide range of applications [8]. Tracking the physical locations of sensor nodes enhances the overall performance of WSNs, leading to improved data analysis, optimized resource allocation, and efficient network management [9]. However, achieving accurate localization in WSNs is challenging because of the inherent characteristics of wireless communication and the dynamic nature of the network environment [10]. Factors such as signal attenuation, multipath fading, and environmental obstructions can introduce errors and uncertainties into the localization process [11].

Different techniques, including range-based, range-free, machine learning, and optimization algorithms, have been explored for WSN node localization [12]. However, these localization techniques face challenges in certain scenarios, particularly in indoor environments, where Global Positioning System (GPS) solutions may not be suitable owing to their high hardware costs, power consumption, and poor performance [13]. To address the localization requirements of WSNs in indoor environments, researchers have turned to alternative techniques, including communication protocols such as Zigbee [14] and 6LoWPAN [15], along with optimization algorithms. These protocols

The associate editor coordinating the review of this manuscript and approving it for publication was Emanuele Lattanzi.

offer low-power, low-cost, and low-data-rate communication solutions, making them well suited for WSNs in indoor settings [16]. Moreover, these protocols provide a means for nodes to exchange localization-related information, such as distance measurements and anchor node positions [17], allowing optimization algorithms to utilize this information for accurate node localization [18].

Optimization algorithms offer a powerful approach to enhance the localization process in WSNs by leveraging mathematical optimization techniques to obtain optimal solutions [19]. These algorithms aim to optimize localization accuracy, scalability, computational complexity, and robustness [20]. By formulating the localization problem as an optimization task, these algorithms can effectively exploit the available measurements and constraints to accurately estimate the positions of the sensor nodes [21].

Several surveys have been conducted to explore WSN node localization techniques, with a focus on 3D localization in underwater networks [10], [22] to comprehensively overview 2D and 3D WSN network architectures employing various localization techniques, including mobile anchors, machine learning, mathematical models, and meta-heuristics [12]. Although these surveys provide valuable insights, they often lack detailed discussions on the specific localization algorithms used, challenges faced in the localization process, and the absence of proposed solutions to these challenges [10], [12], [22], [23]. Furthermore, the use of optimization algorithms for localization has not been thoroughly explained [9], leaving a gap in the literature regarding a detailed examination of optimization techniques tailored to WSN node localization.

This study aims to fill these gaps by presenting a comprehensive review of the optimization algorithms used for WSN node localization. Unlike previous surveys, we delved deeper into the intricacies of optimization techniques, including evolutionary algorithms, swarm intelligence, metaheuristic approaches, and other optimization-based methods, with a focus on their application in achieving accurate and efficient localization within WSNs. Our main contributions are as follows.

a) Offering a detailed analysis of optimization algorithms for WSN node localization, highlighting their strengths, and addressing the gaps in algorithmic discussion.
b) Identifying and examining challenges in using optimization for WSN localization, such as computational complexity and noisy data, were previously less explored.
c) Incorporating the latest advancements in optimization for WSN localization, providing an updated overview of the field, and filling gaps left by prior surveys.
d) Suggesting actionable solutions for enhancing optimization algorithms in WSN localization, focusing on efficiency and cost-effectiveness in response to issues noted in earlier surveys.

We include several acronyms used in this study in Table 1. Furthermore, Figure 1 illustrates the scope of this survey and its categorization. The remainder of this paper is organized as follows. Section II analyzes the current survey on WSN node localization. Section III highlights the architecture of a WSN, the importance of localizing WSNs, and localization strategies, and discusses WSN node localization techniques. In Section IV, we discuss optimization Algorithms for WSN Node Localization, and present a survey of recent research in this domain. Section V presents a thorough examination of the optimization algorithms for WSN node localization. Section VII addresses open issues and proposes solutions related to the optimization of WSN node localization. Finally, Section 8 concludes the paper.

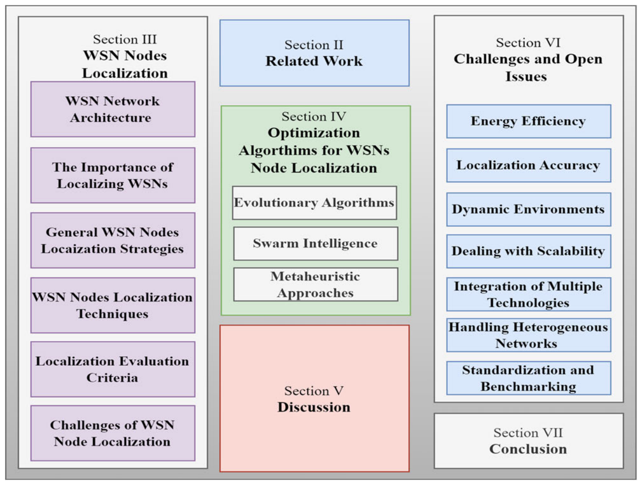

FIGURE 1. The classification of this survey.

II. RELATED WORK

This section summarizes recent surveys gathered from previous review studies, highlighting the current state of digital care and its associated challenges. It also offers insights into the future direction of digital care. Table 2 presents a summary of these surveys, outlining their contributions, scope, and limitations.

Overall, the related works discussed contribute valuable insights into the topic of WSN node localization. However, there are common limitations across these references, including a lack of details on the specific localization algorithms used, challenges faced, and proposed solutions. Enhancing the level of detail in these areas would provide a more comprehensive understanding and facilitate practical implementation in WSN localization scenarios. Therefore, in this study, further details of the localization process for WSNs nodes, particularly through the use of optimization techniques, will significantly enhance the understanding of the topic. Optimization techniques play a crucial role in determining optimal solutions for WSN node localization, considering factors such as accuracy, energy efficiency, and scalability. Moreover, employing optimization techniques in WSN localization poses certain challenges that must be

TABLE 1. List of abbreviations.

Abbreviations	Full form
WSNs	Wireless Sensor Networks
GPS	Global Positioning System
RSSI	Received Signal Strength Indicator
ToA	Time of Arrival
TOF	Time of Flight
TDoA	Time Difference of Arrival
AoA	Angle of Arrival
d	distance
Δd	the difference in distances
c	the speed of signal propagation
Δt	the difference in arrival times
SVM	Support Vector Machines
k-NN	k-Nearest Neighbors
LSE	Least Squares Estimation
MLE	Maximum Likelihood Estimation
PSO	Particle Swarm Optimization
RMSE	Root Mean Square Error
NLOS	Non-Line-of-Sight
GA	Genetic Algorithms
GP	Genetic Programming
ACO	Ant Colony Optimization
SA	Simulated Annealing
TS	Tabu Search
GWO	Grey Wolf Optimizer
WOA	Whale Optimization Algorithm
SLnO	Simulated L annealing-based Neighborhood Optimization
EAs	Evolutionary algorithms
NGC	Neighborhood Grid Cluster
3DGAIDV	3D Genetic Algorithm based Improved Distance Vector
IAGA	Improved Adaptive Genetic Algorithm
DE	Differential Evolution
NS-IPSO	Node Segmentation with Improved Particle Swarm Optimization
HPSOVNS	Hybrid Particle Swarm Optimization with Variable Neighborhood Search
VNS	Variable Neighborhood Search
ISAPSO	self-adaptive inertia weight particle swarm optimization
EGWO	Enhanced Grey Wolf Optimizer
PCCSO	Parallel Compact Cat Swarm Optimization
ML	Machine Learning
CSO	Cat Swarm Optimization
ELM	Extreme Learning Machine
MSO	Multi-Swarm Optimization
CHs	Cluster Heads
FPSOTS	Fuzzy Particle Swarm Optimization with Tabu Search
ES	Early Stopping
ECS	Enhanced Cuckoo Search
SOCTO	Selective Opposition Class Topper Optimization
BPNN	the BP Neural Network
APIT	Approximate Point-in-Triangulation
Bat-SA	Bat algorithm optimized by Simulated Annealing
QABA	Quantum Annealing Bat Algorithm
TSNMRA	Tunicate Swarm Naked Mole-Rat Algorithm
SDN	Software-Defined Networking
QoS	Quality of Service

addressed for practical implementation. One challenge is the computational complexity associated with optimization algorithms, which often require significant computational resources and time. This can limit their applicability in resource-constrained WSN environments. Additionally, the presence of noisy or incomplete sensor measurements can further complicate the optimization process, potentially leading to suboptimal localization results. To overcome these challenges, the proposed solutions can focus on optimizing the efficiency and performance of localization algorithms.

The subsequent overview outlines the distinctive features of our review article, which differentiate it from other reviews and surveys. This paper focuses on:

a) Further details on the localization process for WSNs nodes, particularly through optimization techniques, will enhance our understanding and practical implementation.
b) The challenges of using optimization in WSN localization include the computational complexity and the presence of noisy or incomplete sensor measurements.
c) The latest research findings are surveyed to optimize efficiency, accuracy, and reliability in WSN node localization, considering the unique characteristics of WSNs and addressing the challenges associated with optimization.
d) The proposed solutions can focus on developing tailored optimization algorithms for WSN localization, incorporating data-fusion techniques, and leveraging machine learning for adaptive optimization.

III. WSN NODES LOCALIZATION

This section focuses on WSNs node localization and delves into various aspects associated with this topic. We examine the key elements of WSN localization, starting with an exploration of the network architecture. We discuss the importance of localization in WSNs and highlight the different techniques employed for node localization. Furthermore, we delve into the evaluation criteria used to assess the effectiveness of the localization techniques. Finally, we address the challenges that arise in achieving accurate node localization within WSNs. Through this comprehensive analysis, we aimed to provide a thorough understanding of WSN node localization and its underlying components.

A. WSN NETWORK ARCHITECTURE

The architecture of a WSN comprises a network of interconnected WSN nodes that collaboratively gather and transmit data wirelessly, [24] as illustrated in Figure 2. These WSN nodes are typically small resource-constrained devices with sensing, processing, and communication capabilities [25]. They are deployed in a specific area to form a self-organizing network. The network may also include anchor nodes or base stations responsible for collecting and aggregating data from WSN nodes [26].

Based on Figure 2, the network employs the 6LoWPAN protocol, which facilitates automated IP distribution using

TABLE 2. Comparison of WSNs Localization Techniques.

Ref	WSNs node localization	Contribution	Scope	Limitations
[10]	√	Categorized WSN nodes localization based on anchor nodes' nature and range-free/range-based approaches	3D localization for underwater WSN networks.	Lack of details about the localization algorithms used
[12]	√	Providing a comprehensive overview of different localization techniques such as Mobile Anchor, Machine Learning, Mathematical Models and Meta-heuristics.	2D and 3D of WSNs network architecture.	Lack of details about the challenges and proposed solutions
[22]	√	Providing an overview of the network structure, routing technology, and localization evaluation criteria.	underwater wireless sensor networks	Failure to provide proposed solutions to the challenges discussed
[23]	√	Provide a detailed explanation of the use of metaheuristic algorithms to solve localization problem	WSNs network architecture.	Lack of details about how the metaheuristic algorithms work, failure to discuss challenges and failure to discuss any solutions
[5]	√	Discussed and analyzed WSNs node localization in mobility and dense-multipath environments.	WSNs network architecture.	Lack of details such as the reviewed papers analyses, challenges discussion and solutions.
[9]	√	Presents an extensive analysis of localization techniques and introduces a hierarchical taxonomy based on the presence of offline training in localization, distinguishing between self-determining and training-dependent approaches	2D and 3D of WSNs network architecture.	There is no explanation for the use of the optimization algorithms to localize WSN nodes.
Our Work	√	Provides a comprehensive review of optimization algorithms for WSN node localization, including evolutionary algorithms, swarm intelligence, and metaheuristic approaches. Evaluates algorithms based on accuracy, scalability, computational complexity, and robustness. Discusses challenges specific to optimization in WSN localization and proposes novel solutions.	2D and 3D of WSNs network architecture.	Addresses limitations of previous surveys by providing detailed insights into optimization techniques, including computational complexity and handling of noisy/incomplete sensor measurements.

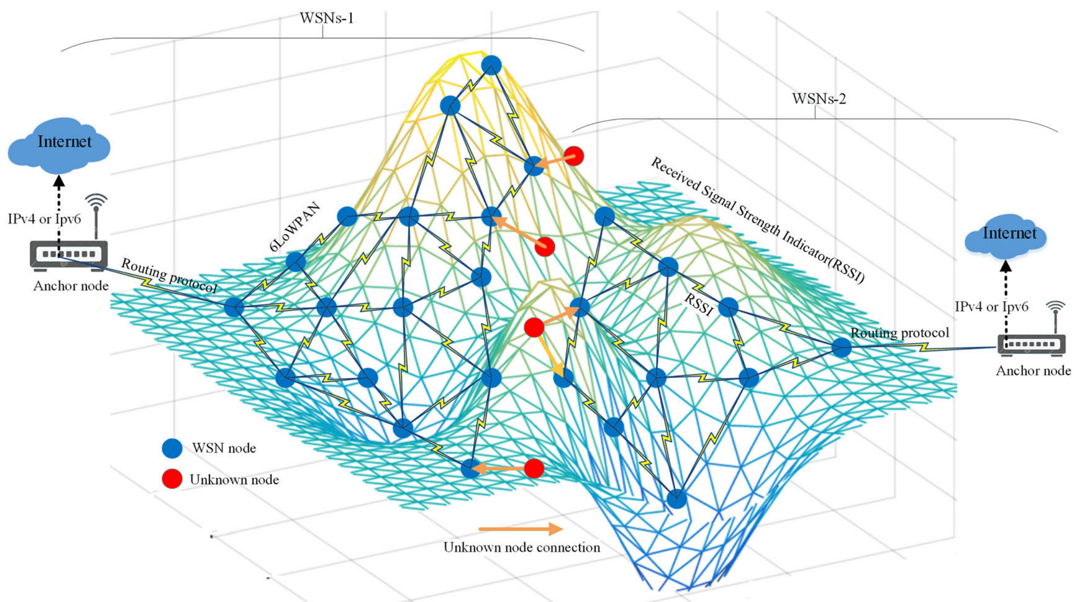

FIGURE 2. The WSNs network architecture.

IPv6 and establishes a hierarchical relationship (parent-child) for data transmission from the peripheral sensors to the access point [14]. The optimal positioning of WSN nodes is essential to ensure proximity between WSN nodes, thereby enabling efficient Received Signal Strength Indicator (RSSI) maintenance, reduced power consumption, and sustained data rates [27]. Hence, providing suitable WSN node locations is important for the effectiveness of this network configuration. The basic WSNs architecture is summarized as follows.

a) WSNs Nodes: WSN nodes play a vital role in the functioning of a WSN and can be classified into sensor, anchor, and unknown nodes [28]. These nodes serve as the fundamental building blocks of the network, encompassing essential components, such as a sensing unit, processing unit, memory, communication interface, and power source [29]. With embedded sensors, these nodes gather data from the surrounding environment, process it locally, and transmit it to other nodes or base stations within the network. In particular, anchor nodes employ either GPS technology or manual configuration to accurately determine their own coordinates, which in turn aids in localizing unknown nodes within the network [30]. Moreover, each sensor node establishes connections with its neighboring nodes, thus enabling the determination of its precise location [31].

b) Network Topology: WSNs offer the flexibility to adopt diverse network topologies such as star, tree, mesh, and hybrid configurations [32]. The selection of an appropriate topology is driven by the specific requirements and objectives of the application. In star topology, sensor nodes establish direct communication links with a central base station, enabling efficient data exchange. In contrast, a tree topology facilitates hierarchical data aggregation, allowing for structured and scalable information processing. The mesh topology enhances the fault tolerance by providing multiple communication paths, thereby ensuring reliable data transmission [33]. Hybrid topologies combine different network structures to leverage their respective advantages and optimize network performance.

c) Communication Protocols: Effective communication protocols play a critical role in ensuring efficient data transmission and network management within WSNs. These protocols operate at various layers of the network stack, encompassing physical, data link, network, transport, and application layers [34]. Prominent protocols employed in WSNs include IEEE 802.15.4, Zigbee [14], and WirelessHART. These protocols facilitate reliable and energy-efficient communication among the sensor nodes, enabling seamless data exchange. It is worth highlighting that the network topology depicted in Figure 2 is specifically based on the 6LoWPAN network, utilizing the IEEE 802.15.4 protocol to establish communication links.

B. THE IMPORTANCE OF LOCALIZING WSNS

Localization provides numerous benefits for WSNs. By strategically deploying sensors or nodes and accurately determining their locations, network coverage can be optimized, leading to enhanced data accuracy [35]. Localization is particularly vital in scenarios where specific areas or regions require focused monitoring or targeted actions [36]. By combining the precise positions of WSN nodes with the network topology, the localization process empowers WSNs to achieve optimal data collection, efficient routing, and effective network management, thereby improving overall network performance and functionality [37].

Furthermore, localization plays a significant role in the implementation of adaptive power-management strategies for WSN nodes [38]. With the knowledge of their precise locations, nodes can dynamically adjust their transmission power levels based on their distance to the base station or neighboring nodes [39]. This adaptive power management approach effectively reduces energy wastage by avoiding excessive power consumption during long-range transmission. By achieving a balance between energy consumption and network connectivity through dynamic power adjustments, the nodes can optimize energy usage within the WSN [40]. Consequently, this reduction in energy consumption not only extends the lifetime of the network but also enhances its overall energy efficiency, allowing for sustained and prolonged operation of the WSN [34]. The previous discussion regarding the importance of WSN node localization can be summarized as a set of points, as shown in Figure 3.

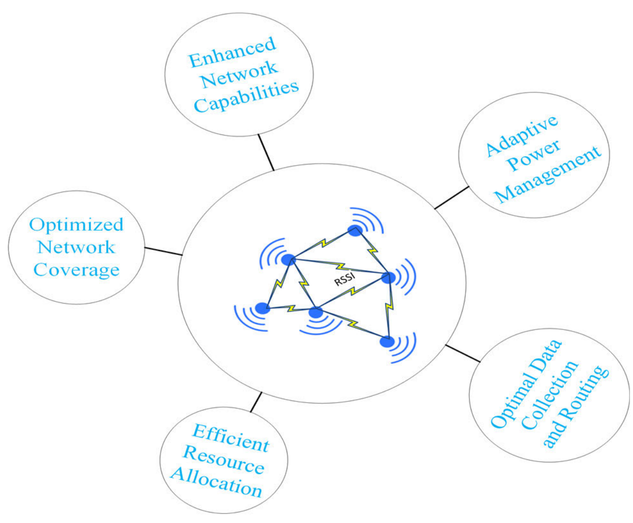

FIGURE 3. The importance of WSNs nodes localization.

C. GENERAL WSN NODES LOCALIZATION STRATEGIES

In the context of WSN node localization, the two main localization strategies are range- and range-free. Geometric, machine learning, and optimization methods can be applied within these two strategies to estimate node positions. In this subsection, the main localization strategies based on their methodology are discussed, including ranging-based such as Received Signal Strength (RSS) localization and ranging-free localization.

1) RANGE-BASED STRATEGY

Range-based localization techniques utilize distance measurements such as the Received Signal Strength Indicator (RSSI), Time of Arrival (ToA), Time Difference of Arrival (TDoA), and Angle of Arrival (AoA) to estimate node positions [41]. These techniques leverage Trilateration and Triangulation to determine node locations [42]. Examples include GPS and anchor nodes with known positions.

a) Trilateration: Trilateration is a commonly used range-based localization method that involves measuring the distance between a node and three or more anchor nodes with known positions. The distance can be determined using techniques such as time-of-flight (TOF), RSSI, or TDOA [43]. The TOF is based on the measurement of the time taken for a signal to travel from a source node to a destination node [42]. By determining the speed of signal propagation, the distance between the nodes can be calculated using Equation1:

$$d = Speed\ of\ Light \times Time\ of\ Flight \tag{1}$$

where d represents the distance. Moreover, RSSI utilizes the strength of the received signal to estimate the distance between nodes. The signal strength typically decreases with increasing distance owing to path loss and signal attenuation. The RSSI value was measured at the receiving node, and distance estimation was performed using an empirical relationship between the signal strength and distance. The exact relationship can vary depending on the specific wireless technology and environmental conditions, and it involves measuring the time difference between the arrival of a signal at different reference nodes [43]. By determining the speed of signal propagation, the difference in arrival times can be converted into differences in distances. The TDOA can be expressed mathematically as:

$$\Delta d = c \times \Delta t \tag{2}$$

where Δd represents the difference in distance, c represents the speed of signal propagation, and Δt represents the difference in arrival times. The basic principle of trilateration is that the position of a node can be uniquely determined by intersecting circles (in 2D) or spheres (in 3D) centered at anchor nodes with radii equal to their respective measured distances. The node positions can be estimated by determining the intersection points.

However, Trilateration assumes that the distance measurements are accurate and that there is line-of-sight or sufficient connectivity between nodes, [44] as illustrated in Figure 4. It is important to have a sufficient number of anchor nodes to ensure reliable position estimation. Nevertheless, Trilateration is sensitive to measurement errors and inaccuracies, multipath interference, and non-line-of-sight conditions, which can affect localization accuracy [45].

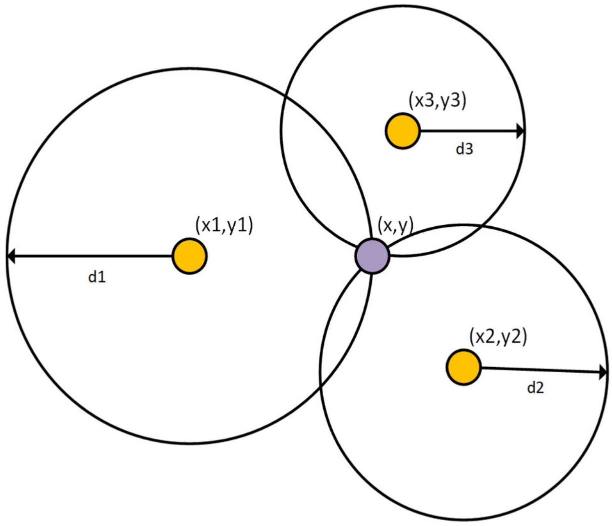

FIGURE 4. The Trilateration technique.

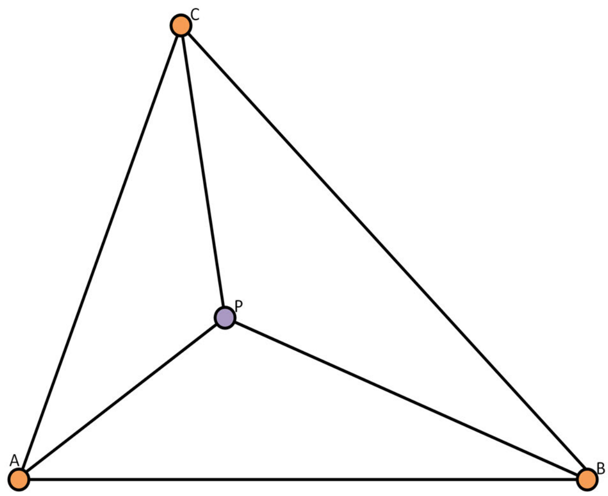

FIGURE 5. The Triangulation technique.

b) Multilateration: Multilateration extends trilateration to a three-dimensional space. Similar to trilateration, it uses distance measurements to estimate the node positions [10]. The method assumes that the reference nodes are within the communication range of the unknown node and that the distances between them can be accurately measured. However, instead of intersecting circles or spheres, multi-acceleration considers the intersection of the spheres centered around the anchor nodes [17]. With at least four anchor nodes, the position of an unknown node can be determined by determining the intersection points of the spheres. Nevertheless, it is important to note that multi-aeration assumes ideal conditions, including accurate distance measurements, absence of measurement errors, and line-of-sight or sufficient connectivity between the unknown node and the reference nodes [46].

c) Triangulation: Triangulation is another range-based localization method that estimates the position of a node based on the angles formed by the node and multiple anchor nodes with known positions [47]. This method uses the geometric principles of triangulation to determine the location of a node. The position can be calculated using trigonometric calculations by measuring the AOA or TDOA between the node and anchor nodes [48]. The AOA method calculates the angle of arrival using trigonometric principles. Consider Figure 5, where a target node sends a signal received by three reference nodes: A, B, and C. The arrival angles at these nodes were θA, θB, and θC, respectively. Given the known positions of the reference nodes, the position of the target node was estimated by solving a system of equations derived from the trigonometric relationships between the angles and node positions. Assuming that the reference nodes are at positions (x_A, y_A), (x_B, y_B), and (x_C, y_C), the system of equations using AOA for triangulation is

$$tan\,(\theta_A) = \frac{y - y_A}{x - x_A} \tag{3}$$

$$tan\,(\theta_B) = \frac{y - y_B}{x - x_B} \tag{4}$$

$$tan\,(\theta_C) = \frac{y - y_C}{x - x_C} \tag{5}$$

These equations must be solved simultaneously to determine the coordinates (x, y) of a target node. However, Triangulation requires at least three anchor nodes to obtain a unique position estimate. It is less affected by range measurement errors than trilateration, because it relies on angle measurements [49]. Moreover, Triangulation may be influenced by factors such as multipath interference, signal attenuation, and the need for accurate angular measurements [50].

Furthermore, the choice between Trilateration, Multilateration and Triangulation depends on factors such as the availability of distance or angle measurements, environmental characteristics, and application requirements [51], [52].

2) RANGE-FREE STRATEGY

Range-Free Localization techniques operate based on the principle of utilizing relative position information rather than precise distance measurements [53]. These techniques aim to estimate the positions of sensor nodes in a WSN based on connectivity patterns, hop counts, and proximity information gathered from neighboring nodes [54]. These techniques leverage Centroid Localization, DV-Hop, and Amorphous Localization to determine the node locations [55].

a) Centroid-based method: Anchor nodes with known positions are strategically placed in the network [56]. Each sensor node collects signal strength or hop count information from its neighbors and computes its estimated position using the centroid of the neighboring anchor nodes [57]. The centroid is calculated by taking the average of the anchor node positions.

b) DV-Hop method: The DV-Hop algorithm uses hop count information to estimate the distances between the nodes. Initially, the anchor nodes were deployed at known positions [58]. Each sensor node determines its distance from the anchor nodes based on hop count values [59]. By utilizing the anchor nodes as reference points, the sensor node's position is estimated using multi-acceleration or trilateration techniques.

c) Amorphous localization: The basic principle of amorphous localization is to exploit the network connectivity graph to infer the relative positions of nodes. It leverages the information obtained from the connectivity patterns and RSSI of neighboring nodes to estimate the positions of unknown nodes [60]. The underlying assumption is that nodes within proximity have a stronger connectivity and share similar network characteristics.

In addition, to enhance the accuracy and robustness of range-free localization, modern research has proposed various improvements, such as incorporating localization algorithms with mobility prediction [61], deploying mobile anchor nodes [62] using directional antennas [63], and integrating additional contextual information such as RSSIs and AOA measurements [64].

3) HYBRID LOCALIZATION STRATEGY

Hybrid localization techniques combine the strengths of multiple localization methods, such as range-based and range-free techniques, to improve the accuracy and reliability of node localization in WSNs and overcome the limitations and challenges associated with individual localization methods [65]. In hybrid localization, multiple sources of information are integrated to estimate the positions of WSN nodes [66]. This includes range measurements, connectivity information, environmental constraints, and additional contextual data. Some common hybrid localization approaches include the following.

a) Range-Based and Range-Free Fusion: This approach combines range-based techniques such as trilateration with range-free techniques such as amorphous localization [67]. By integrating distance measurements from range-based methods with connectivity information from range-free methods, a hybrid technique can achieve better localization accuracy and reliability [66].

b) Sensor Data Fusion: In this approach, sensor data collected from different modalities, such as range measurements, signal strengths, angle measurements, and environmental information, are fused together to estimate the node positions [68]. The fusion process can be performed using statistical techniques, machine-learning algorithms, or optimization methods to integrate and interpret different types of sensor data [69], [70].

TABLE 3. Comparison of WSNs Localization Techniques.

Localization Technique	Technique	Flexibility	Applicability	Data Requirements	Limitation
Geometric Methods	Distance or angle-based estimation between anchor and unknown nodes	Limited flexibility	Suitable for scenarios with known anchors and accurate measurements	Requires knowledge of anchor positions and precise measurements	Dependence on an adequate number of anchor nodes sensitive to noise and obstacles
Machine Learning Methods	Algorithms and statistical models trained on labeled data	High flexibility to handle complex relationships	General	Requires labeled training data and computational resources	Computational complexity and training time may suffer from overfitting
Optimization Techniques	Formulating localization as an optimization problem	High flexibility to incorporate constraints and objectives	General	Requires knowledge of network parameters and optimization objectives	Computational complexity for large-scale networks better handling of constraints and trade-offs

c) Cooperative Localization: Cooperative localization involves collaboration among nodes in the network to collectively estimate their positions. Nodes exchange information such as range measurements, connectivity data, or relative positioning to improve the accuracy of individual position estimates [71]. Cooperative localization can be achieved through distributed algorithms or centralized coordination. Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) are commonly employed in collaborative localization approaches [53].

D. WSN NODES LOCALIZATION TECHNIQUES

WSNs employ various localization techniques to determine the spatial coordinates of WSNs nodes within the network. These techniques can be broadly categorized as follows:

1) GEOMETRIC METHODS

Geometric methods in localization leverage mathematical principles and geometric relationships to estimate the positions of nodes in a WSN [72].

a) Range-Based Geometric Methods: These methods utilize measured range information (e.g., distance, angle, and time) between nodes to estimate positions. Common geometric algorithms used in range-based localization include Trilateration, Multilateration, and Triangulation [73]. Trilateration involves intersecting circles or spheres to determine the position of the node, whereas multilateration extends this concept to multiple range measurements. Triangulation uses angle measurements to calculate positions based on the laws of cosines and sines.

b) Range-Free Geometric Methods: Range-free geometric methods do not rely on direct range measurements but instead use geometric relationships between nodes. One popular range-free geometric algorithm is the Centroid Localization method, which estimates a node's position as the centroid of its neighboring reference nodes [74]. Other approaches include the DV-hop algorithm and Amorphous Localization algorithm, which utilize hop distances or relative coordinates to estimate node positions.

2) MACHINE LEARNING METHODS

Machine learning methods involve training models on collected sensor data to learn patterns and make predictions regarding the location of the node [75].

a) Range-Based Machine Learning Methods: In range-based localization, machine learning algorithms can be applied to improve the accuracy and mitigate noise. For example, Support Vector Machines (SVM), k-nearest neighbors (k-NN), and Random Forests can be used to learn the mapping between range measurements and node positions [76]. These models can then predict the positions of unseen nodes based on their range measurements.

b) Range-free machine-learning methods: Range-free localization can also benefit from machine-learning techniques. One common approach is to use supervised learning algorithms to train models on labeled data where the node positions are known [77]. These models can then be used to predict the positions of the unlabeled nodes based on features such as signal strength, connectivity patterns, or environmental characteristics.

3) OPTIMIZATION METHODS

Optimization methods aim to determine the optimal node positions that satisfy certain criteria, such as minimizing localization errors or maximizing network connectivity [23].

a) Range-based Optimization Methods: In range-based localization, optimization methods can be used to minimize localization errors. This can be formulated as an optimization problem, where the objective function minimizes the difference between the measured and estimated ranges [78], [79], [79]. Techniques such as least-squares estimation (LSE), Maximum Likelihood Estimation (MLE), and Nonlinear Optimization methods (e.g., Levenberg-Marquardt) can be employed to solve these optimization problems and obtain accurate node positions.
b) Range-Free Optimization Methods: Range-free localization also benefits from these optimization methods. These methods aim to maximize the network connectivity or coverage by optimizing the deployment of nodes [80], [81]. Optimization algorithms, such as GAs, PSO, or Simulated Annealing, can be used to find the optimal node positions that satisfy the connectivity or coverage objectives.

Table 3 presents a comparison of these techniques to summarize each of the aforementioned techniques. Each technique is evaluated based on various factors including technology, flexibility, applicability, data requirements, and limitations.

E. LOCALIZATION EVALUATION CRITERIA

The evaluation of localization techniques in WSNs necessitates the utilization of localization evaluation criteria, which play a critical role in assessing the performance and effectiveness. These criteria facilitate the quantitative measurement and assessment of factors such as the accuracy, reliability, efficiency, and overall quality of localization results [82]. By employing these evaluation criteria, researchers and practitioners can compare various localization techniques, gain insights into their limitations, and identify avenues for enhancement. The following section highlights some of the commonly employed localization evaluation criteria that contribute to a comprehensive evaluation framework for WSN localization techniques [83].

1) ACCURACY: It measures how closely the estimated positions of the sensor nodes align with their true positions. It is typically evaluated using metrics such as the mean error, Root Mean Square Error (RMSE), or Euclidean distance between the estimated and true positions. A higher accuracy indicates better localization performance.
2) PRECISION: Precision assesses the consistency and repeatability of the localization results. It measures the variation or spread of the estimated positions around the true positions. Precision can be evaluated using metrics such as the standard deviation or interquartile range. Lower precision values indicate better localization precision.
3) Coverage refers to the percentage of sensor nodes that are successfully localized within the target area. It measures the effectiveness of a localization technique for localizing a high proportion of nodes. A higher coverage indicates better localization coverage.
4) ROBUSTNESS: Robustness evaluates the resilience of a localization technique to various environmental factors, noise, and errors. It assesses how well the technique performs under challenging conditions such as harsh environments, signal interference, or sensor failures. Robustness can be evaluated by introducing perturbations or variations in the system and measuring the impact on localization accuracy.
5) SCALABILITY: This assesses the ability of a localization technique to handle large-scale WSNs with an increasing number of sensor nodes. It measures computational efficiency, memory usage, and communication overhead of a technique as the network size increases. A scalable localization technique can provide accurate results without significant performance degradation in large networks.
6) NETWORK LIFETIME: The longevity of a localization system network is determined by node energy consumption and the ability of nodes to work efficiently, contributing to the overall stability of monitoring.
7) ENERGY EFFICIENCY: Energy efficiency evaluates the energy consumption of the localization technique. It considers the power requirements for node localization, communication, and processing. Energy-efficient techniques minimize energy consumption to prolong network lifetime and reduce the need for frequent battery replacements or recharging.
8) COMPUTATIONAL COMPLEXITY: Computational complexity measures the computational resources required by a localization technique, such as the processing power, memory, and algorithmic complexity. Lower computational complexity indicates a more efficient technique that can be implemented on resource-constrained sensor nodes.
9) REAL-TIME PERFORMANCE: Real-time performance evaluates the responsiveness and timeliness of a localization technique in providing localization results. It measures the time required to estimate positions and update node locations. Real-time localization is crucial for time-sensitive applications where up-to-date information is required for decision-making.

Table 4 provides a comparative analysis of the evaluation criteria for general localization techniques. The ratings assigned to each criterion are relative and dependent on the type of technology employed as well as specific implementation and scenario considerations.

F. CHALLENGES OF WSNS NODE LOCALIZATION

Although WSN node localization offers numerous benefits, several challenges need to be addressed for successful implementation [84], [85]. These challenges arise because of the unique characteristics and constraints of WSNs [36]. The following are some of the key challenges associated with WSN node localization.

TABLE 4. Comparison of evaluation criteria on general localization techniques.

Localization Technique	Accuracy	Precision	Coverage	Robustness	Scalability	Network Lifetime	Energy Efficiency	Computational Complexity	Real-time Performance
Geometric	High	High	Limited	Limited	Limited	Moderate	Moderate	Low to Moderate	Limited
Machine Learning (ML)	Moderate	Moderate	Moderate	Moderate	High	Moderate	Moderate to High	High	Moderate to High
Optimization	High	High	High	High	High	High	High	Moderate to High	High

1) LIMITED RESOURCES: WSN nodes are typically resource-constrained in terms of processing power, memory, communication capabilities, and energy supply. These limitations impose constraints on the complexity and computational requirements of localization algorithms. Efficient utilization of limited resources is crucial to ensure accurate and energy-efficient localization regardless of the deployment environment.
2) SIGNAL PROPAGATION: The propagation of signals in a wireless medium is influenced by environmental factors such as path loss, multipath fading, interference, and obstacles. These factors introduce uncertainties and variations in the signal strength, time of flight, and angle of arrival measurements, which can affect the accuracy of localization. Dealing with signal propagation challenges and mitigating their impacts are essential for reliable localization.
3) NON-LINE-OF-SIGHT (NLOS) CONDITIONS: In many practical scenarios, WSN nodes may be located in areas with obstructed line-of-sight paths or multipath propagation. NLOS conditions can lead to distorted signal measurements and introduce localization errors. Developing robust techniques that can handle NLOS conditions and accurately estimate the node positions is a significant challenge.
4) SCALABILITY: WSNs often consist of a large number of nodes deployed over a wide area, which makes scalability a critical challenge. Localization algorithms need to be scaled efficiently to handle large network sizes and maintain reasonable computation and communication overhead. Accurate and timely localization in large-scale deployments is essential for effective operation of WSNs.
5) MOBILITY AND DYNAMIC NETWORK TOPOLOGY: In some WSN applications, nodes may be mobile or deployed in environments in which the network topology changes dynamically. Node mobility and dynamic topology pose challenges for localization algorithms because nodes may change their positions or connections frequently. Adapting localization techniques to handle mobility and dynamic topologies is necessary for maintaining accurate node positions.
6) LOCALIZATION ACCURACY: Achieving a high localization accuracy is a fundamental challenge in WSNs. Various sources of errors, including measurement errors, environmental conditions, and computational limitations, can affect the accuracy of localization. Improving the accuracy of localization techniques through advanced algorithms, error-mitigation strategies, and calibration methods is an ongoing research area.
7) POWER MANAGEMENT: Efficient power management is crucial for maximizing the lifespan of WSN nodes in any environment. Optimizing the energy consumption and extending the operational life of nodes are important considerations. Techniques such as duty cycling, sleep scheduling, and energy harvesting can help overcome energy restrictions and prolong the operational lifespans of WSN nodes.

However, optimization techniques surpass geometric and machine-learning methods for WSN localization [86]. By leveraging mathematical optimization algorithms, optimization techniques can be used to handle complex problems and address challenges such as node positioning and energy efficiency [87], [88]. They are adaptable to various network configurations and environmental conditions. Unlike geometric methods, which rely on calculations and assumptions, optimization techniques provide a flexible framework for incorporating diverse objectives into a single fitness function [87]. Machine learning methods require extensive training data and face scalability issues [89], whereas optimization techniques offer an efficient approach for resource-constrained WSNs [90]. Thus, optimization techniques are preferred because of their adaptability, scalability, and optimization capabilities in WSN localization.

IV. OPTIMIZATION ALGORITHMS FOR WSN NODE LOCALIZATION

In the context of WSNs node localization, various optimization algorithms are commonly employed to obtain optimal or near-optimal solutions for node localization. We divided these algorithms into three prominent categories of optimization algorithms used in this field: evolutionary algorithms, swarm intelligence, and metaheuristic approaches, as illustrated in Figure 6. It is possible that these categories may overlap but are based on the most obvious technology in each reviewed work.

Evolutionary Algorithms (EAs) [91] such as GA [92], [93] and Genetic Programming (GP) focus on genetic-inspired operators and evolutionary processes to guide the search for optimal solutions. Swarm intelligence algorithms such as PSO [94] and Ant Colony Optimization (ACO)

TABLE 5. Ackley Multimodal parameters.

Name	Type	Expression equation	Dim	Scope	$f_{\min}$	x_{min}
Ackley	*multimodal*	$f_{10}(x) = -20\exp\left[-\frac{1}{5}\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right] - \exp\left[\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right] + 20 + e$	10, 20, 30	[-32, 32]	0	(0, 0, …, 0)

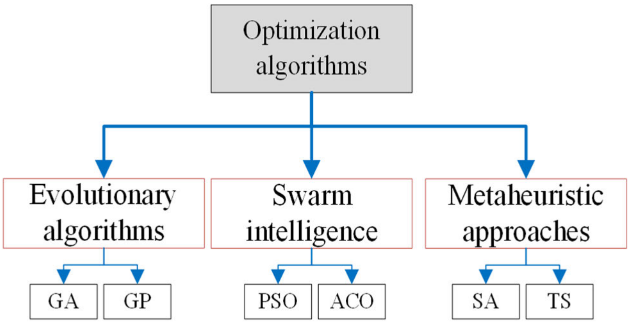

FIGURE 6. Optimization algorithms categories for WSN nodes localization.

[19] emphasize decentralized interactions and collective intelligence to navigate the solution space. Metaheuristic approaches such as Simulated Annealing (SA) [66], [95] and Tabu Search (TS) [96] provide general-purpose frameworks to guide the search by combining different problem-solving strategies. The selection of the optimization category depends on various factors, including the problem domain, problem characteristics, and desired trade-offs between exploration and exploitation, as well as solution quality and computational efficiency [97]. Furthermore, evaluating the performance of the optimization techniques is necessary to choose the type of algorithm used. The run time and convergence of optimization techniques are important factors to consider when evaluating the performance of the compared techniques [98], [99]. The run time refers to the amount of time it takes for an optimization technique to converge to a solution. A technique that requires a long time to converge may not be practical for real-world problems, especially those that require quick decision-making. On the other hand, a technique that converges quickly may be preferable, but it may sacrifice solution quality for speed. Convergence refers to the process by which an optimization technique approaches a solution [100]. A technique that converges quickly implies that it finds a solution in a relatively small number of function evaluations. A technique that converges slowly, on the other hand, may require a large number of function evaluations to find a solution. To evaluate the performance of an optimization technique, metrics such as the objective function value, number of function evaluations, and run time are typically used [100], [101]. The objective function value measures the closeness of the technique's solution to the true optimal solution. The number of function evaluations measures the number of times the objective function is evaluated using the technique. The runtime measures how long it takes for the technique to converge to a solution.

To demonstrate the performance of the optimization algorithm samples, such as (PSO, GA, Grey Wolf Optimizer (GWO) [101], simulated annealing-based neighborhood optimization (SLnO) [102], and Whale Optimization Algorithm (WOA) [103], [104]) on an Ackley model, the parameters of [44], [57], [105], and [106] which are listed in Table 5. The convergence of the algorithm for different dimensions is illustrated in Figure 7. Figure 8 illustrates the running costs of these optimization algorithms under the same model.

As illustrated in Figures 7 and 8, when comparing the most important localization evaluation criteria, such as the convergence and time parameters for the optimization algorithms (PSO, GA, GWO, SLnO, and WOA), several factors contributed to the observed differences. The faster convergence of the PSO and GWO algorithms can be attributed to their efficient exploration and exploitation capabilities facilitated by their swarm-based approaches. These algorithms employ mechanisms, such as velocity updates and social interactions, which enable rapid convergence towards promising solutions. In contrast, the SLnO and WOA algorithms prioritize exploration, often employing diverse search strategies and extensive solution space exploration. Although this leads to slower convergence rates, it enhances their ability to discover globally optimal solutions and overcome local optima. In terms of time efficiency, the faster execution of the PSO and GA algorithms can be attributed to their simplified operations and reduced computational overhead. GWO, SLnO and WOA algorithms, on the other hand, involve more complex operations and population-based approaches, resulting in longer computational times. Consequently, the choice of the optimization algorithm should consider the trade-off between the convergence speed, solution quality, and available computational resources.

A. EVOLUTIONARY ALGORITHMS

Evolutionary algorithms (EAs) are composed of key components that are applied to the WSN localization process, enabling effective optimization of node positions. These components include population initialization, fitness evaluation, selection, genetic operators (crossover and mutation), and termination conditions, [107] as illustrated in Algorithm 1.

The illustrated for each algorithm 1 steps explained as follows:

a) The population initialization step involves randomly generating an initial set of candidate solutions that

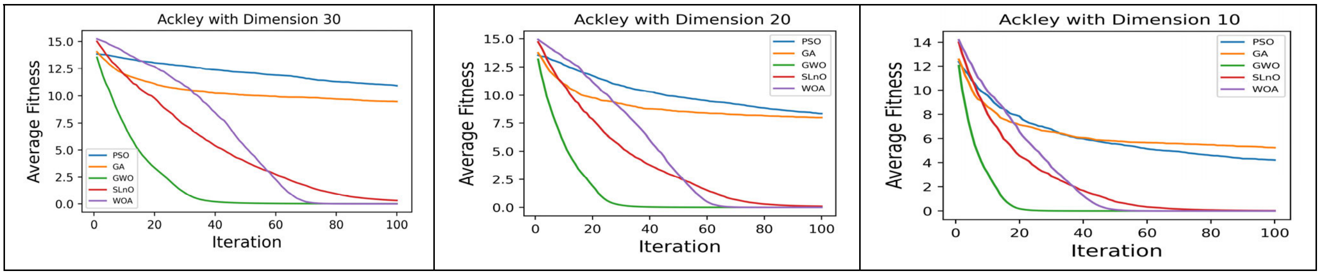

FIGURE 7. Convergence of compared algorithms on unimodal benchmark functions.

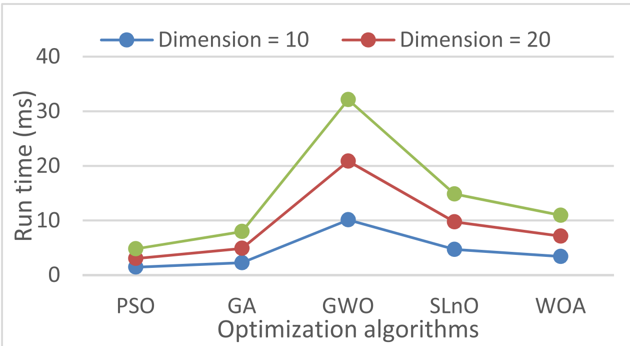

FIGURE 8. Optimization algorithms running cost.

Algorithm 1 EAs for WSN Localization

1. Start
2. Initialize Population with random candidate solutions
3. Evaluate Fitness for each candidate solution using a fitness function
4. While Termination Condition is not met, do:
    5. Select parent solution based on their fitness values
    6. Apply Genetic Operators to generate offspring solutions
        6.1 Crossover
        6.2 Mutation
    7. Evaluate Fitness of the offspring solutions
    8. Select Next Generation (best solutions)
9. End While
10. Best Solution as the localized positions of the WSN nodes
11. End

represent the potential node positions. These solutions are evaluated using a fitness function that measures the quality of localization estimates.

b) The fitness evaluation considers factors such as the distance between nodes, connectivity information, signal strength, and anchor node measurements.

c) Selection is a crucial step in EAs, in which individuals with higher fitness values are chosen as parents for the next generation. Various selection strategies, such as tournament selection or roulette-wheel selection, can be employed to balance exploration and exploitation in the search space.

d) Genetic operators, including crossover and mutation, mimic biological evolution by combining and altering the candidate solutions to create new offspring. Crossover involves combining the genetic information of two parent solutions to produce one or more offspring with a combination of their characteristics. Mutation introduces random changes to the offspring to explore new regions in the search space and prevent premature convergence.

e) To ensure convergence, termination conditions were defined, such as the maximum number of generations or a threshold value for the fitness function. Once the termination conditions are satisfied, the algorithm stops, and the best solution found during the evolutionary process is considered to be the localized positions of the nodes.

However, it is important to consider the weaknesses associated with EAs. Premature convergence can occur when the algorithm converges to suboptimal solutions before reaching a global optimum. Computational complexity can pose challenges, particularly for complex problems with numerous variables and constraints, limiting their applicability in certain scenarios [108]. EAs lack problem-specific knowledge, relying solely on the exploration and exploitation of the search space, which may lead to inefficient searches and suboptimal solutions. The performance of EAs is highly sensitive to parameter values, requiring careful selection to avoid issues such as poor or premature convergence. In addition, EAs may face difficulties when applied to high-dimensional problems owing to the exponential growth of the search space [66], [109], [110]. Unlike some optimization techniques, EAs do not provide guaranteed convergence to the global optimum, making their convergence behavior unpredictable.

Several recent studies have used or improved this AE category for the localization of WSN nodes. Some of these studies are summarized in Table 6. The [111], [112] proposed clustering method is called Neighborhood Grid Cluster (NGC) to address the localization of WSNs node challenges and reduce energy consumption. The NGC approach utilizes a GA optimization process to improve the efficiency and reliability of localization algorithms (to estimate the position of the target node). Moreover, the fitness function considers the energy consumption, node connectivity, and Euclidean distance. The results demonstrate that the proposed NGCGA outperforms other methods in terms of energy consumption, number of alive nodes, and network coverage. However, this study has certain limitations, including node constraints, distance errors, and mobility. In the same context of using a clustering technique along with GA, [113] introduced a GA-based mobile sink technique for energy-efficient data routing in WSNs. The algorithm divides the network into clusters of rectangular shapes with a sink movement trajectory passing through each cluster. The GA determines the optimal data collection points on the trajectory for each cluster, thereby minimizing the data transmission energy. The optimization framework also considers the optimal location of cluster head nodes based on the residual energy, distance, and previous selection count.

In the same context as using GA, [81], [93] the proposed GADV-Hop algorithm combines GA with the DV-Hop localization approach to enhance the accuracy of node localization in WSNs. GADV-hop restricts the feasible region of the initial population and improves the quality of the population. By utilizing this restrained population feasible region, the algorithm achieves a more accurate localization of unknown nodes and significantly faster convergence than previous algorithms. In addition, the authors of [114] proposed a 3D genetic algorithm-based Improved Distance Vector (3DGAIDV), which incorporates a GA to further enhance the localization accuracy in three-dimensional wireless sensor networks. This algorithm introduces several enhancements to improve the localization accuracy. First, the hop size of the anchor nodes is adjusted using a correction factor. The line search algorithm was employed to determine the optimal hop size for the anchor nodes. This modification enables more precise distance calculation between the target and anchor nodes. The algorithm also addresses localization errors by introducing the concept of coplanarity, which excludes the coplanar anchor nodes from the localization process. To further enhance the localization accuracy, a GA was integrated by utilizing bounded population feasible regions. Successful localized target nodes are upgraded to assist anchor nodes, expanding the localization coverage and accuracy in subsequent rounds. However, the 3DGAIDV complexity is high.

In addition, the authors of [115] recognized the limitations of the standard GA, such as the order of crossover and mutation operations, which can lead to suboptimal solutions. To overcome this, they introduced an improved strategy that switched the order of these operations. In addition, they dynamically adjusted the probability of crossover and mutation based on the evolution of the population. These modifications aim to better utilize the advantages of crossover and mutation operators and enhance the accuracy of node positioning. Through experimental evaluation, the proposed Improved Adaptive Genetic Algorithm (IAGA) demonstrated competitiveness and superiority in terms of benchmark functions and WSN node localization, showcasing the effectiveness of the improvements made to GA. In the same context of using IAGA, the authors [116] combined an IAGA and 2D hyperbolic localization algorithm to enhance the accuracy of traditional DV-Hop. The proposed algorithm addresses the limitation of low localization accuracy in DV-Hop by introducing a modified factor to improve the distance estimation between anchor nodes and unknown nodes. It also incorporates the 2D hyperbolic localization algorithm to further refine the estimated coordinates of the unknown nodes. Additionally, the initial population area of the genetic algorithm was reduced to improve the convergence speed, stability, and localization accuracy.

Different techniques combining GA and Differential Evolution (DE) were proposed in [117]. GA-DE combines the strengths of GA and DE, utilizing GA's selection and crossover operators, and DE's powerful mutation operator. By leveraging the strengths of both algorithms, GA-DE offers improved performance in terms of location estimation accuracy, convergence, and scalability. However, while GA-DE offers improvements, it may still face challenges in handling highly complex optimization problems efficiently. Moreover, the performance of GA-DE depends heavily on the parameter settings, and finding the optimal set of parameters can be time-consuming. Furthermore, the authors in [118] introduced a hybrid approach that combines the GA and the Firefly algorithm to tackle the optimization problem of localization. Their method involved initializing a population of fireflies using the most robust solution obtained from the GA, and iteratively evolving this population to search for the optimal global answer. The proposed model employs various operators, including attractiveness, reach, and acceleration, to facilitate the movement of fireflies towards brighter individuals. Fitness measurement took into account factors such as illumination, attractiveness, distance, and movement of fireflies.

Another method that uses GA to improve the WSNs node localization accuracy was proposed in [119]. This study introduced a novel approach for indoor localization using RSSI quantization and GA. The GA, based on an elitist preservation strategy, was employed to optimize the division of the network into rings and determine the ring widths (threshold optimization). Ambiguities in the areas that appeared were addressed using a density-based clustering method [120]. Moreover, to achieve accurate target localization, a two-stage centroid-localization algorithm was proposed.

Furthermore, a comprehensive comparison was conducted to assess the standard method, accuracy, power consumption, computational complexity, localization time, and simulation coverage of all reviewed localization optimization algorithms. A comparison between the localization algorithms discussed in this subsection and those described in the other subsections is presented in Table 9.

B. SWARM INTELLIGENCE

Swarm intelligence is another category of optimization algorithms commonly used in WSN localization [35]. It is inspired by the collective behavior of social insect colonies, where individual agents interact with each other and the environment to achieve a common goal. In the context of WSN localization, swarm intelligence algorithms leverage the principles of self-organization, decentralized decision making, and cooperation among nodes to estimate the positions of unknown nodes [121], [122].

One of the prominent swarm intelligence algorithms used for WSN localization is PSO. PSO is based on the concept of a swarm of particles that move through a search space to find optimal solutions. Each particle represents a potential solution and its position in the search space corresponds to a candidate localization solution. The particles communicate and update their positions and velocities based on their own experiences and the collective information obtained from other particles in the swarm. The WSN localization process using PSO is described by Algorithm 2 [123].

Algorithm 2 PSO for WSN Localization

1: Initialize swarm of particles with random positions and velocities
2: Initialize local best positions for each particle
3: Initialize global best position for the swarm
4: while termination criteria are not met do:
5: for each particle in the swarm do:
6: Evaluate fitness of the particle's current position
7: Update local best position of the particle if necessary
8: Update global best position of the swarm if necessary
9: Update velocity of the particle based on current velocity, cognitive component, and social component
10: Update position of the particle based on its velocity
11: end for
12: end while
13: Return the best position found as the solution

Based on Algorithm2, the localization process of this type consists of the following main processes:

a) Initialization: The swarm of particles is initialized by randomly assigning positions and velocities within the search space. The position of each particle represents the potential localization solution.
b) Fitness Evaluation: Evaluate the fitness of each particle's position by comparing the estimated coordinates with the true coordinates of the sensor nodes. The fitness function quantifies the quality of the localization solution, which is typically based on the error between the estimated and true coordinates.
c) Update Particle Velocities and Positions: Update the velocity and position of each particle based on its previous velocity, position, and best positions found by itself and its neighboring particles. This step allows particles to explore the search space while considering their own experiences and the collective knowledge of the swarm.
d) Termination Criteria: Check if the termination criteria are met. This can be based on the maximum number of iterations or if a satisfactory solution is found. If the termination criteria are not met, the Fitness Evaluation is returned.
e) However, the performance of swarm intelligence algorithms for WSN localization can be influenced by factors such as the swarm size, network topology, neighborhood structure choice, and fitness function design [21]. Careful consideration and tuning of these parameters are required to ensure effective localization results.

Because PSO provides the best convergence and the least time cost (fast computing and high precision), it is expected that its use and development will be greater than the rest of the categories. Table 7 shows comparisons between these studies. PSO was used [79], [124] to localize three-dimensional WSNs. Moreover, a PSO-WAN localization analysis was presented in [125] for PSO to select the optimal PSO parameters. These results demonstrate that the PSO variant with a constriction coefficient and a ring topology outperforms other variants and topologies and is superior to the second-order cone programming algorithm. For underwater WSN node localization, the authors of [95] used PSO to predict the locations of unknown mobile nodes. The beacon nodes were localized using a range-based PSO algorithm, and their velocities were calculated. The unknown nodes were then located using mobility prediction based on the spatial correlation of the mobility of underwater objects.

For PSO enhancement by reducing the fitness function cost and improving the accuracy, [126] proposed a novel technique called Node Segmentation with Improved Particle Swarm Optimization (NS-IPSO) to enhance the sensor node localization accuracy in areas with obstructions. By dividing sensor nodes into segments and improving the fitness function (considering the minimum hop counts of each anchor node) and the particle swarm optimization algorithm, the proposed scheme achieves higher accuracy compared to state-of-the-art methods. The simulation results demonstrated its effectiveness, particularly in scenarios with obstacles. However, further validation in real-world scenarios, consideration of different deployment conditions, and investigation of scalability and efficiency are required. Moreover, [94] we introduce an improved method for optimizing the WSNs coverage using an enhanced PSO algorithm. The proposed approach addresses the issue of the random deployment of WSN nodes by dynamically adjusting the inertia coefficient and introducing a mutation operator to enhance the standard PSO algorithm. These modifications aim to improve the global convergence speed, increase the particle diversity, and prevent the algorithm from becoming trapped in local optima. However, it is important to consider potential limitations such as the sensitivity of the algorithm to parameter settings and the need for further validation in real-world deployment scenarios. In the same context as improving PSO, [127] presented a modern and efficient algorithm called Hybrid Particle Swarm Optimization with Variable Neighborhood Search (HPSOVNS) for localization in outdoor WSNs. The

TABLE 6. Comparison of AEs Optimization algorithms.

Refs	Technique	Optimization Algorithm	Evaluation Criteria	Advantages	Limitations
[111]	Clustering	GA	Energy consumption, Number of alive nodes, Network coverage	Outperforms other methods in energy consumption, number of alive nodes, and network coverage	Node constraints, distance errors, and mobility
[112]	Clustering	GA	Energy consumption, Localized Distance Error, Coverage Connection	Outperforms other methods in energy consumption, number of alive nodes, and network coverage	Node constraints, distance errors, and mobility
[113]	Hierarchical Clustering	GA	Data transmission energy, Network Lifetime, Data Transmission Reliability	Minimizes data transmission energy through optimal data collection points and cluster head node selection based on residual energy, distance, and selection count	Not scalable
[93]	DV-Hop	GA	Localization accuracy, Convergence speed	Achieves more accurate localization and faster convergence through restrained population feasible region	Computational complexity
[81]	DV-Hop	GA	Localization accuracy	Enhances localization accuracy in three-dimensional WSNs through adjustment of anchor nodes' hop size, coplanarity exclusion, and bounded population feasible regions	High complexity
[114]	DV-Hop	3DGAIDV	Localization accuracy improvement in three-dimensional WSNs	Adjusted hop size, coplanarity consideration, bounded population feasible regions.	High complexity
[115]	DV-Hop	Adaptive Genetic Algorithm (IAGA) through Improving strategy for crossover and mutation	Benchmark functions, WSN node localization	Improves accuracy of node positioning by modifying the order of crossover and mutation operations and dynamically adjusting their probabilities	Error caused by topological structure, Node layout impact, Single-objective optimization
[116]	2D hyperbolic localization algorithm	Adaptive Genetic Algorithm (IAGA)	Localization accuracy, Convergence speed	Enhances accuracy of traditional DV-Hop through improved distance estimation, modified factor, and reduced initial population area	Anchor node ratio and upgrade process, Uniform node distribution assumption
[117]	DE is based on the concept of a populace of trajectories	GA-DE hybrid	Location estimation accuracy, Convergence, Scalability	Combines strengths of GA and DE for improved performance in location estimation, convergence, and scalability	Challenges in handling complex optimization problems efficiently, parameter optimization
[118]	Firefly localization algorithm	Hybrid GA	Location estimation accuracy, Convergence	Utilizes strengths of GA and Firefly algorithm for optimal global answer search and movement facilitation	Depends on parameter settings, time-consuming parameter optimization
[119]	RSSI quantization, Density-based clustering	GA	Localization accuracy	Optimizes network division, solves ambiguity, and achieves accurate target localization	Real-world implementation challenges, Deployment optimality

algorithm combines PSO with Variable Neighborhood Search (VNS) to optimize the objective function, which is the last mean squared range error of neighboring anchor nodes. The algorithm utilizes the RSSI to calculate the interior distances between the WSN nodes.

In addition, [128] an improved PSO algorithm called improved self-adaptive inertia weight particle swarm optimization (ISAPSO) is used to overcome the issue of losing diversity and getting trapped in local optima in standard PSO. The ISAPSO algorithm is based on the

TABLE 7. Comparison of Swarm intelligence Optimization algorithms.

Refs	Environment	Optimization Algorithm	Evaluation Criteria	Advantages	Limitations
[124]	Localization in 3D WSNs	PSO	Localization accuracy	Improved positioning accuracy in 3D WSNs	Not cover dynamic environments
[79]	Localization in mobile 3D WSNs	PSO	Localization errors	addresses the mobility aspect of WSNs	Increased computational complexity
[125]	Localization in 2D WSNs	PSO parameter selection for PSO-WANs localization	PSO performance analysis	Superiority over other variants and topologies	Analysis only
[95]	Underwater WSN localization	PSO	Localization accuracy, mobility prediction	Improved localization accuracy and coverage in underwater WSNs	Dependency on ranging accuracy
[126]	Sensor node localization with obstacles	NS-IPSO	Localization accuracy, obstacle scenarios	Higher accuracy compared to state-of-the-art methods	Need for validation in real-world scenarios, scalability and efficiency considerations
[94]	Optimization of WSNs coverage	Enhanced PSO algorithm	Coverage improvement	Improved global convergence speed and particle diversity	Sensitivity to parameter settings, need for validation in real-world scenarios
[127]	Localization in outdoor WSNs	HPSOVNS	Localization accuracy, mean squared range error	Improved localization accuracy using RSSI	Small-scale experiment
[128]	Localization in WSNs	ISAPSO	Positioning accuracy, power consumption, real-time performance	Better performance in positioning accuracy, power consumption, and real-time performance	Dependency on ranging accuracy
[129]	Localization in 2D & 3D WSNs	AMCMPSO	Positioning accuracy, power consumption, real-time performance	Better performance in positioning accuracy, power consumption, and real-time performance	Dependency on ranging accuracy
[130]	Deployment of WSNs on 3D surfaces	EGWO	Optimization precision, convergence performance	Improved optimization precision and convergence performance on benchmark functions	Need for validation in real-world scenarios, scalability and efficiency considerations
[103]	Wireless network localization	Improved whale optimization algorithm	Localization accuracy	More accurate and consistent localization of unknown nodes in wireless networks	lack of real-world validation and scalability analysis
[109]	Localization in WSNs using CSO	PCCSO	Localization accuracy, memory consumption	Improved local search capability, reduced memory usage	Sensitivity to parameter settings
[131]	Sensor energy optimization and WSN connectivity	Fuzzy clustering with PSO	Energy optimization, WSN connectivity	Improved energy optimization and WSN connectivity	Lack of extensive analysis and evaluation
[132]	Range-free localization using hybrid model	Fuzzy logic system with centroid algorithm and ELM	Localization accuracy, adaptability	Adaptive and robust location estimation in different scenarios	need for further investigation on scalability
[80]	Multi-objective optimization for DV-Hop localization	PSO	Localization accuracy, computation time, localization error variance	Improved localization accuracy compared to single objective optimization	Does not cover irregular topologies and varying node densities
[133]	Wireless network localization	Range-based localization, node segmentation, PSO	Localization precision, obstacle scenarios	Enhanced localization precision, particularly in areas with obstacles	Performance dependence on network topology and anchor node distribution

convergence conditions of PSO and retains the simplicity, ease of implementation, and low-parameter adjustments of the original algorithm. In addition, the initial search space of PSO is optimized considering the characteristics of WSN localization, and a comparative analysis with two other PSO algorithms demonstrates that the ISAPSO algorithm achieves better performance in terms of positioning accuracy, power consumption, and real-time performance under different conditions such as beacon node proportions, node densities, and ranging errors. However, the performance of the ISAPSO algorithm is likely influenced by the accuracy of the ranging measurements based on RSSI. If the ranging accuracy is low, this may lead to less accurate localization results. Within the realm of enhancing PSO, the work presented in [129] marks a noteworthy stride in achieving precise and efficient sensor node localization within WSNs-6LoWPANs. The authors proposed the Adaptive Mean Center of Mass Particle Swarm Optimizer (AMCMPSO), an innovative algorithm that adapts parameters to significantly enhance the search efficiency and convergence speed. Through comprehensive simulations, the study demonstrates the remarkable performance of AMCMPSO, boasting an average improvement rate of 99.86% and consistently maintaining a localization error below 1.34 cm. Even in intricate 3D environments, AMCMPSO exhibits robustness, sustaining coverage rates that exceed 87%. This work not only contributes to the refinement of PSO, but also holds promise for advancing the accuracy and efficiency of sensor node localization in wireless sensor networks, particularly within the context of WSNs-6LoWPANs.

Another technique proposed to improve GWO was presented in [130] for the Enhanced Grey Wolf Optimizer (EGWO) for deploying WSNs on 3D surfaces. EGWO enhances the exploitation and exploration ability of the GWO by dividing the grey wolf population into two parts responsible for outer layer and inner layer encircling and introducing tent mapping. This improves the convergence and optimization precision of the algorithm. This study also presented an improved method for determining the perceived blind zone and calculating the WSNs coverage area on simple and complex 3D surfaces using a combination of grid and integral techniques. The simulation results showed that the EGWO outperformed the original GWO and three existing variants in terms of optimization precision and convergence performance on benchmark functions. However, it is important to validate the effectiveness of EGWO in real-world scenarios and consider its scalability and efficiency in large-scale WSN deployment. Moreover, [103] an improved version of the whale optimization algorithm incorporating the exploratory move operator from the Hooke-Jeeves local search method for wireless network localization is proposed. Furthermore, [109] presented the Parallel Compact Cat Swarm Optimization (PCCSO) algorithm, a heuristic approach based on the Cat Swarm Optimization (CSO) algorithm. The PCCSO addresses the limitations of CSO, including poor convergence and high memory consumption, by introducing three separate communication strategies and the concept of compactness. These enhancements improve the algorithm's local search capability and reduce the memory usage. In addition, PCCSO is applied to the DV-Hop localization algorithm in wireless sensor networks, resulting in improved localization accuracy and memory efficiency.

Another technique that depends on fuzzy clustering and PSO was proposed in [131] to address the issue of sensor energy optimization and improve WSNs connectivity. However, this study does not provide an extensive analysis or evaluation of the performance of the method with larger network sizes or more complex scenarios. Moreover, [132] presented a hybrid method for improving range-free localization by integrating a fuzzy logic system into the centroid algorithm and optimizing it using an Extreme Learning Machine (ELM) technique. The proposed hybrid model combines the strengths of both approaches, allowing adaptive and robust location estimation in different scenarios. Adaptive weights based on node ratios within the sensing coverage and coverage range were used, and the resultant force vectors with particle swarm optimization enhanced efficiency in heterogeneous topologies. The technique shows promise in addressing the limitations of traditional range-free localization methods and offers improved performance for WSN localization. Moreover, related to range-free localization, the authors in [80] converted the traditional DV-Hop from a single-objective optimization algorithm to a multi-objective optimization algorithm. PSO was used as the optimization algorithm. Related to Range-based localization, [133] the proposed technique combines range-based localization, sensor node segmentation, and PSO. By segmenting the nodes into a restricted set of anchor nodes (clusters) and using PSO with an improved fitness function, the localization precision is enhanced, particularly in areas with obstacles. The advantage of this approach is its ability to achieve higher accuracy in estimating the locations of unknown nodes compared with recent PSO-based methods. However, it is important to note that the performance of the proposed scheme may depend on the specific network topology, number, and distribution of the anchor nodes. Further evaluation and experimentation are required to validate its effectiveness in different scenarios and to determine its scalability and efficiency in large-scale sensor networks.

C. METAHEURISTIC APPROACHES

Metaheuristic algorithms have gained significant attention in the field of WSN localization owing to their ability to efficiently address complex optimization problems [66], [110], [134]. Unlike conventional optimization techniques that rely on problem-specific knowledge, metaheuristics offer a more general approach to guide the search process [135], [136]. Metaheuristic algorithms are well suited for WSN localization because they can handle the challenges posed by the dynamic and unpredictable nature of wireless sensor networks.

One of the key advantages of metaheuristic algorithms is their ability to effectively explore and exploit the search space. This is particularly crucial in WSN localization, where the node positions are often unknown and must be estimated accurately [137]. Metaheuristics such as Simulated Annealing (SA) and Tabu Search (TS) use adaptive search strategies to balance exploration (searching for new solutions) and exploitation (exploiting promising regions of the search space). This balance allows the algorithms to escape local optima and converge towards the global optimum, thereby providing accurate and robust localization results. Another significant advantage of metaheuristics is their flexibility and ease of implementation. Metaheuristic algorithms do not require explicit mathematical models for the problem, making them applicable to a wide range of WSN localization scenarios [138].

Metaheuristic algorithms typically consist of key components that enable them to navigate the search space efficiently [139]. The key components of metaheuristic algorithms applied to WSN localization are illustrated in Algorithm 3.

Algorithm 3 Metaheuristic for WSN Localization

Input: WSN node positions and localization objectives
1. Initialize Population with random candidate solutions
2. Evaluate Fitness for each candidate solution using a fitness function
3. Set the current best solution as the solution with the highest fitness
4. Repeat until termination condition is met:
   5. Generate new candidate solutions based on search operators
   6. Evaluate Fitness for each new candidate solution
   7. Update the current best solution if a better solution is found
8. Return the best solution found as the localized positions of the WSN nodes
// Note: The specific search operators and termination conditions will depend on the chosen metaheuristic algorithm.

Based on Algorithm 3, the localization process of this type consists of the following main processes:

a) Initialization: The process begins by initializing a population of candidate solutions that represent potential node positions. These solutions can be generated randomly or based on heuristics.
b) Fitness Evaluation: Each candidate solution is evaluated using a fitness function that assesses the quality of the localization estimates. The fitness function considers factors, such as distance measurements, connectivity information, signal strength, and anchor node measurements, to determine the fitness of a solution.
c) Exploration and Exploitation: Metaheuristic algorithms strike a balance between exploration and exploitation to search the solution space effectively. Exploration involves exploring new regions of the search space to discover better solutions, whereas exploitation focuses on exploiting promising regions to refine and optimize solutions. This balance is critical for achieving an accurate and robust localization.
d) Search Strategy: Metaheuristic algorithms employ specific search strategies to navigate the solution space. These strategies may include local search operators, such as neighborhood exploration or local optimization, and global search operators, such as diversification or intensification. The combination of these strategies helps the algorithm efficiently explore the solution space and converge towards optimal or near-optimal solutions.
e) Iteration and Termination: The algorithm iterates through multiple generations or iterations, generating new candidate solutions and updating the population based on fitness evaluation. Termination conditions are defined to determine when the algorithm should be stopped. These conditions can be the maximum number of iterations required to reach a specific fitness threshold or a predefined time limit.
f) Solution Selection: At the end of the execution of the algorithm, the best solution found during the optimization process is selected as the localized position of the WSN nodes. The selection process ensures that the algorithm converges towards the most promising solution that satisfies the localization objectives.

However, like any optimization technique, metaheuristics have some limitations. One common concern is the stochastic nature of these algorithms, which can lead to variable performances across different runs [5], [99]. The results obtained by metaheuristics may not always be reproducible and require multiple runs to ensure solution robustness and stability. In addition, the performance of metaheuristic algorithms can be sensitive to parameter settings, necessitating careful tuning and optimization of these parameters for optimal results. Moreover, their generic nature allows researchers and practitioners to adapt to various constraints, objectives, and network conditions without significant modifications. This adaptability is particularly advantageous in real-world WSN localization applications, where the environments may change and the number of nodes and anchor nodes can vary. Table 8 shows some comparisons of the reviewed studies.

Reference [140] proposed a technique that combines Multi-Swarm Optimization (MSO) with TS to improve energy efficiency and routing optimization in large-scale WSNs. By selecting efficient Cluster Heads (CHs), the system enhances the network lifespan and routing optimization. The technique offers advantages such as an increased number of clusters formed, enhanced energy dissipation, improved lifetime computation, and reduced packet loss and end-to-end delay. However, clustering introduces additional overhead owing to the need for cluster formation, cluster head selection, and intercluster communication. Moreover, a different technique was proposed in, [141] which is a fuzzy logic-based Tabu Search (TS) algorithm model for increasing the lifetime of WSNs by optimizing energy consumption and distance. However, the complexity and sensitivity of the algorithm to parameters, as well as its potential limitations in handling network dynamics, should be considered. Furthermore, in the same context as using fuzzy logic, the authors in [96] presented a new approach called Fuzzy Particle Swarm Optimization with Tabu Search

TABLE 8. Comparison of Metaheuristic Optimization algorithms.

Ref	Technique	Optimization Algorithm	Evaluation Criteria	Advantages	Limitations
[140]	Clustering	Multi-swarm optimization combined with TS	Increased number of clusters, enhanced energy dissipation, improved lifetime computation, reduced packet loss and end-to-end delay	Improved energy efficiency and routing optimization, extended network lifespan	Additional overhead due to clustering: cluster formation, cluster head selection, and inter-cluster communication
[141]	Clustering	Fuzzy logic-based TS	Lifetime improvement, energy consumption reduction	Enhanced lifetime of WSNs, optimized energy consumption and distance	Algorithm complexity, sensitivity to parameters, potential limitations in handling network dynamics
[96]	RSSI	Fuzzy PSO with TS (FPSOTS)	Localization accuracy, convergence performance	Improved indoor localization, faster convergence, better accuracy than existing approaches	dependency on initial solution based on trilateration
[75]	Clustering and routing	Enhanced Cuckoo Search (ECS)	Localization error	Faster convergence, reduced resource utilization, improved search efficiency	Assumes a centralized architecture, limited scalability and applicability in decentralized or distributed WSN environments
[142]	DV-Hop	Selective Opposition Class Topper Optimization (SOCTO)	Average localization error	Improved localization accuracy compared to DV-Hop technique and related approaches	Dependency on beacon node weight for changing hop size
[143]	DV-Hop	Weighted DV-Hop method with simulated annealing	Positioning accuracy	Improved positioning accuracy, better representation of network's average distance through weighted distance estimation	Potential Overfitting
[144]	The static wireless sensor network	Simulated Annealing-based Grey Wolf Optimization	Optimization speed, network coverage, energy consumption, network lifespan prolongation	Improved optimization speed, network coverage, reduced energy consumption, prolonged network lifespan	High computational complexity
[145]	Approximate Point-in-Triangulation	Bat algorithm optimized by Simulated Annealing (Bat-SA)	Localization accuracy	Improved localization accuracy compared to traditional APIT algorithm	Convergence speed may be relatively slow in certain scenarios
[110]	Trilateral localization and Geometric feature	Quantum annealing bat algorithm (QABA)	Convergence speed	Enhanced local and global search capabilities, improved convergence, two-dimensional (2D) and three-dimensional (3D) localization algorithms	Convergence speed may be slow in certain scenarios
[146]	A hexagonal projection approach	Tunicate Swarm Naked Mole-Rat Algorithm (TSNMRA)	Localization accuracy	Target node localization, utilization of virtual anchors, determination of target nodes' coordinates	computational complexity and resource requirements

(FPSOTS) to improve indoor localization in WSNs by enhancing the performance of PSO. The proposed approach incorporates a tabu search to accelerate convergence, and introduces limit and performance checks within the PSO algorithm. Moreover, it utilizes the RSSI method to evaluate the distances between sensors.

Different types of searches were proposed in, [75] called the Enhanced Cuckoo Search (ECS) algorithm. The proposed

TABLE 9. Comparison of the reviewed localization Optimization algorithms.

Ref	Standard Optimization Technique	Accuracy	Energy Consumption	Computational Complexity	Localization Time	Simulation Coverage
[111], [112]	GA	High	Low	Moderate	Short	Wide
[113]	GA	Moderate	Moderate	Moderate	Moderate	Moderate
[81], [93]	GA	High	Low	Moderate	Short	Wide
[114]	GA	High	Moderate	High	Long	Wide
[115]	IAGA	High	Low	Moderate	Short	Wide
[116]	IAGA	High	Low	Moderate	Short	Wide
[117]	GA-DE	High	Low	Moderate	Short	Wide
[118]	Hybrid GA	High	Low	Moderate	Short	Wide
[119]	GA	Moderate	Moderate	Moderate	Moderate	Moderate
[79], [124]	PSO	High	Low	Moderate	Short	Wide
[125]	PSO	High	Low	Moderate	Short	Wide
[95]	PSO	Moderate	Low	Moderate	Moderate	Wide
[126]	NS-PSO	High	Low	Moderate	Short	Wide
[94]	PSO	Moderate	Low	Moderate	Short	Wide
[127]	PSO	High	Low	Moderate	Short	Wide
[19]	PSO	High	Low	Moderate	Long	Wide
[128]	GWO	High	High	Moderate	Short	Wide
[130]	WOA	High	Low	Moderate	Short	Wide
[103]	PSO	High	Low	Moderate	Short	Wide
[109]	PSO	Moderate	Low	Moderate	Moderate	Moderate
[131]	ML and PSO	High	Low	Moderate	Short	Wide
[132]	PSO	High	Low	Moderate	Short	Wide
[80]	PSO	High	Reduced	Moderate	Short	Wide
[133]	TS	High	Low	Moderate	Short	Wide
[140]	TS	High	Low	Moderate	Short	Wide
[141]	TS	High	Low	Moderate	Short	Wide
[96]	CS	High	Low	Moderate	Short	Wide
[75]	TO	High	Low	Moderate	Short	Wide
[142]	SA	High	Moderate	Moderate	Moderate	Moderate
[143]	SA and GWO	High	High	High	Long	Wide
[144]	SA	High	Low	Moderate	Short	Wide
[145]	SA	High	Low	Moderate	Short	Wide
[110]	TS	High	Low	Moderate	Short	Wide

ECS algorithm is based on bio-inspired meta-heuristic algorithms and converts the node-localization problem into an optimization problem. The algorithm incorporates an Early Stopping (ES) mechanism that exits the search loop as soon as the optimal solution is reached, resulting in improved search efficiency and reduced resource utilization. However, the proposed ECS algorithm assumes a centralized architecture, in which all neighboring anchor nodes communicate with a central entity. This may limit the scalability and applicability of the algorithm to decentralized or distributed WSN environments. Moreover, [142] introduced an enhanced version of the DV-Hop algorithm called Selective Opposition

Class Topper Optimization (SOCTO) for localization in WSNs. The technique focuses on optimizing the computation of the average hop size with the weight of the beacon nodes to improve localization accuracy. The proposed algorithm demonstrated superior performance compared to the DV-Hop technique and related approaches in terms of the average localization error.

Different techniques using simulated annealing have been proposed in [143]. In this study, a weighted DV-Hop method that utilizes efficient simulated annealing was used to improve the positioning accuracy of the sensors. The classic DV-Hop algorithm has limited accuracy owing to errors in estimating the average distance between adjacent sensors. The proposed method assigns weights to the average distance of each known node based on their influence on the unknown nodes, resulting in a more accurate representation of the network's average distance. The locations of the unknown nodes are determined by applying an efficient simulated annealing algorithm. The experimental results conducted in MATLAB demonstrate that the proposed method achieves a higher precision in positioning. However, the use of a BP Neural Network (BPNN) for coordinate prediction introduces the possibility of overfitting. Another proposed method [144] established a mathematical model for coverage optimization and incorporated the simulated annealing algorithm into the grey wolf optimization algorithm to enhance its global optimization ability and convergence rate. Their Simulation experiments demonstrated that the proposed algorithm outperforms the particle swarm optimization algorithm and the standard grey wolf optimization algorithm in terms of optimization speed, network coverage, energy consumption reduction, and network lifespan prolongation. However, the computational complexity of the proposed algorithm is high. In addition, regarding the use of the Simulated Annealing method, authors in [145] combined the Approximate Point-in-Triangulation (APIT) localization estimation method with the bat algorithm optimized by Simulated Annealing (Bat-SA). It utilizes multisensor data and emphasizes the utilization of a large number of existing access points (APs) to overcome the inaccuracies in range-based localization in an indoor setting. The proposed Bat-SA algorithm offers improved localization accuracy compared with the traditional APIT algorithm. Additionally, [110] introduced a novel algorithm called the quantum annealing at algorithm (QABA). QABA integrates quantum evolution and annealing strategies into the bat algorithm framework to enhance local and global search capabilities. The algorithm achieves a balance between search exploration and exploitation through tournament and natural selection, ultimately converging to the optimized solution. Moreover, the authors designed two localization algorithms: QABA-2D for two-dimensional space and QABA-3D for three-dimensional space, utilizing trilateral localization and geometric feature principles. However, depending on the complexity of the problem and the quality of the initial solution, the convergence speed of the algorithm may still be relatively slow in certain scenarios.

Furthermore, a hybrid technique that depends on a virtual WSN anchor node was proposed [146]. The Tunicate Swarm Naked Mole-Rat Algorithm (TSNMRA) combined with a single static anchor node. TSNMRA is used for target node localization using a dynamic approach, whereas virtual anchors and a hexagonal projection method are employed to determine the coordinates of the target nodes.

V. DISCUSSION

This study aims to review the optimization algorithms for WSN node localization. The findings of this study can be used to evaluate and compare methods used in this field. In Figures 7 and 8, we compare the evaluations of some standard optimization algorithms. In Table 9, we show a comparison of the proposed optimization techniques reviewed in this paper.

Upon analyzing the table, it can be observed that several techniques are associated with high accuracy and low energy consumption. The most prominent methods that exhibit these characteristics are GA, PSO, and IAGA. These techniques consistently demonstrate high accuracy while maintaining efficient energy consumption for WSN localization. The GA is widely employed in the literature, and it consistently achieves high accuracy levels with low energy consumption. This method utilizes optimization processes to improve the localization accuracy by considering factors such as energy consumption, connectivity, and distance. The GA-based approaches in consistently deliver superior accuracy while consuming minimal energy. PSO is another technique that consistently demonstrates high accuracy and low energy consumption. It uses a population-based optimization algorithm to refine the localization process. The PSO-based approaches in achieved high accuracy levels while maintaining efficient energy consumption, making it a popular choice for WSN localization. In addition, IAGA, an enhanced version of GA, exhibits high accuracy and low energy consumption. It introduces improvements in the genetic algorithm to further enhance the accuracy and reliability. References utilizing IAGA consistently report high accuracy levels while maintaining minimum energy consumption.

The percentage distribution of the discussed localization techniques in WSNs reflects their varying popularity and effectiveness in addressing localization challenges, as shown in Figure 9. PSO has the highest percentage (44.44%) because it is widely utilized and enhanced for WSN localization, demonstrating superior performance in terms of accuracy and convergence speed. GA follows with 30.5%, as it is a popular choice for improving localization accuracy by incorporating optimization processes and considering energy consumption, connectivity, and distance. Other techniques, such as WOA, GWO, TS, and SA, have relatively lower percentages (ranging from 2.7% to 11.11%) but still find applications in specific scenarios to enhance optimization and convergence capabilities. The distribution of percentages reflects the diverse research efforts in leveraging optimization

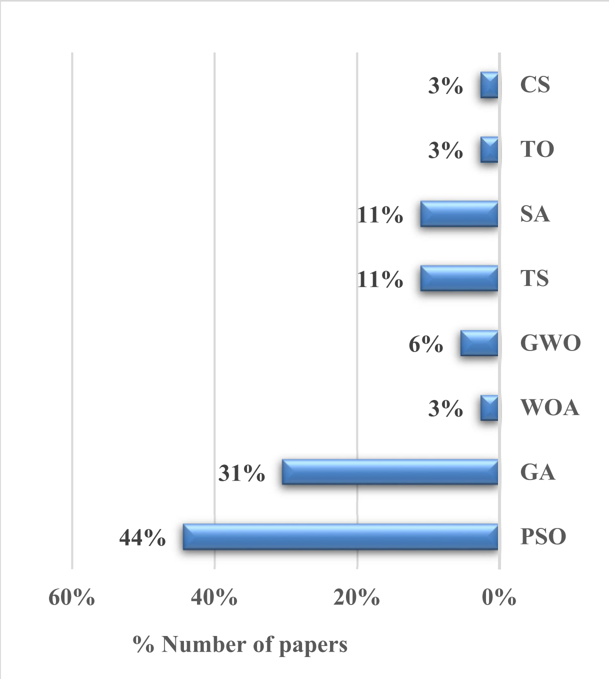

FIGURE 9. Optimization reviewed papers.

algorithms to improve the accuracy, energy efficiency, and convergence of localization techniques in WSNs.

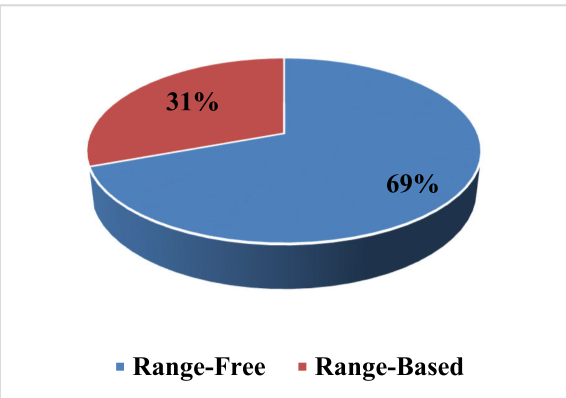

FIGURE 10. WSN nodes Localization strategies used.

Furthermore, Figure 10 indicates that the majority (69.5%) of the discussed techniques focus on range-free localization methods, whereas the remaining percentage (30.5%) is dedicated to range-based localization approaches. RangeF localization techniques do not rely on direct distance measurements but instead utilize connectivity information or other indirect measurements to estimate node positions. These methods often require less resources and are less susceptible to ranging errors. The high percentage of range-free techniques in the discussion suggests their popularity and relevance in WSN localization research. On the other hand, range-based localization methods utilize direct distance measurements, such as time-of-flight or received signal strength, to estimate node positions. These techniques typically provide more accurate localization results but may require additional resources and suffer from ranging errors or signal attenuation.

However, the distribution of percentages reflects the significance and applicability of both the Range-Free and Range-Based localization methods in WSNs. Researchers have explored and developed various techniques within each category to address the unique challenges and requirements of different WSN applications. The choice between the Range-Free and Range-Based approaches depends on the specific constraints, objectives, and environmental conditions of the deployment scenario.

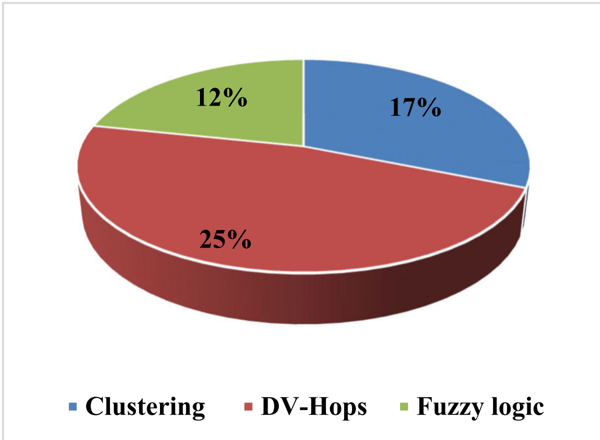

FIGURE 11. Assistive technologies used for localization optimization processes.

Moreover, Figure 11 shows the utilization of assistive techniques in WSN localization. Clustering methods hold a percentage of 16.5%, indicating their moderate usage in optimizing the energy consumption and simplifying the localization process. DV-Hop, a Range-Free localization algorithm, has a higher percentage of 25%, showing its popularity and effectiveness in estimating node positions based on hop count and average distance information. Fuzzy logic techniques, with a percentage of 11.11%, were employed to handle uncertainties and improve accuracy in dynamic environments. The distribution highlights the significance of clustering, DV-Hop, and fuzzy logic in WSN localization, with each technique addressing specific challenges and requirements in different deployment scenarios.

Furthermore, Figure 12 illustrates that 2D localization techniques comprise 75% of the discussed papers, whereas 3D localization techniques account for the remaining 25%. This indicates that the majority of research and focus on WSN localization lies within two-dimensional environments. A higher percentage of 2D localization techniques suggests that they are more prevalent and widely utilized in practical applications. Two-dimensional localization is often straightforward to implement and has been extensively studied owing to its relevance in various real-world scenarios. However, the lower percentage of 3D localization techniques reflects

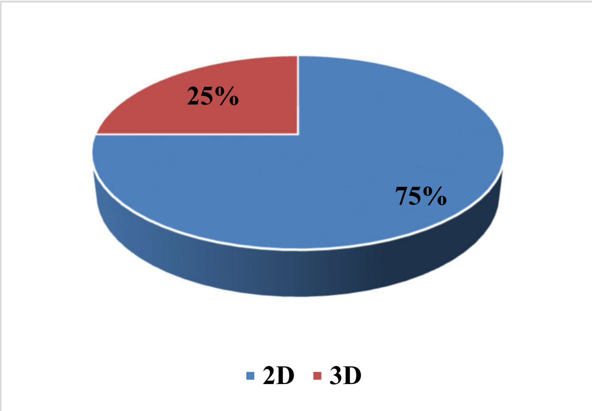

FIGURE 12. Networks architecture used.

their relatively lower adoption and research focus. Three-dimensional localization presents additional complexities compared with 2D localization, such as accounting for height and vertical positioning, which may require specialized algorithms and hardware.

VI. CHALLENGES AND OPEN ISSUES

WSNs node localization has emerged as a prominent research area across multiple fields, garnering significant attention and investigation. Scholars in various relevant domains have made noteworthy contributions to the advancement of WSNs node localization, encompassing enhancements in network topology [147], optimization of location algorithms, and innovative research endeavors, thereby leaving a lasting impact on this research hotspot [148]. However, there are several challenges and open research directions that can be identified in WSN node localization. These include:

1) IMPROVING ENERGY EFFICIENCY: Improving the energy efficiency in WSN localization is a crucial challenge that requires the development of energy-aware algorithms, optimization of data collection and transmission, implementation of duty cycling and sleep scheduling techniques, integration of energy harvesting and energy-aware node deployment strategies [149], designing energy-efficient communication protocols, and exploring hardware and sensing techniques [36]. By minimizing energy consumption without compromising accuracy, the overall lifetime and operational efficiency of WSNs can be maximized, contributing to sustainable and long-lasting localization solutions. It is possible to employ this by transferring the cost of localization operations to another part of the network, such as a software-defined network (SDN) [150], as we will explain later.
2) ENHANCING LOCALIZATION ACCURACY: Enhancing the localization accuracy is a critical aspect that requires further improvement in WSN localization techniques. Although many existing methods achieve high accuracy, there is still room for improvement [35]. Addressing factors such as ranging errors, which can arise from signal attenuation or multipath effects, is crucial for improving accuracy. Additionally, accounting for environmental variations, such as changes in temperature, humidity, or signal interference, can help refine the localization algorithms [151]. Furthermore, considering the presence of obstacles that can obstruct signal propagation and affect distance measurements is essential for enhancing accuracy. Moreover, the improvement of optimization algorithms can lead to more localization processes, making it less costly and more accurate.
3) HANDLING DYNAMIC ENVIRONMENTS: Handling dynamic environments is a significant challenge in WSN localization. WSNs are often deployed in dynamic scenarios in which nodes may move, network topologies can change, and signal propagation conditions may vary [152]. Adapting localization techniques to accommodate these dynamic factors is crucial for maintaining accurate and reliable results. Methods that can track node mobility, dynamically adjust network configurations, and account for varying signal strengths and interference levels can enhance the robustness and adaptability of localization algorithms in dynamic environments [153], [154]. Additionally, incorporating machine learning and data-driven approaches to model and predict changes in the environment can further improve localization accuracy in dynamic WSN scenarios. Therefore, by employing SDN technology, such problems can be solved.
4) DEALING WITH SCALABILITY: As WSNs continue to expand in size and complexity, it is essential to develop localization techniques that can handle large-scale deployments efficiently. Scalability challenges include designing algorithms that can accurately localize a significant number of nodes while minimizing the computational complexity and resource requirements [155]. This involves optimizing the data processing, communication overhead, memory usage, and computational efficiency. Additionally, developing distributed and decentralized localization techniques that can scale with network size and adapt to dynamic network conditions is essential. Exploring novel approaches such as hierarchical localization, cooperative localization, and network partitioning can help address the scalability challenges in WSN localization [8]. By focusing on scalability, researchers can ensure that localization techniques are applicable and effective for real-world large-scale WSN deployments. However, in most studies, protocols such as 6LoWPAN or Zigbee have not been employed in the development of localization processes. Therefore, they should be considered in the development of localization.
5) INTEGRATION OF MULTIPLE TECHNOLOGIES: The Integration of multiple technologies is a promising

research direction for enhancing WSN localization. Investigating the combination of optimization algorithms with other advanced techniques, such as machine learning, artificial intelligence, and data fusion, has the potential to improve the localization performance and robustness [14]. By leveraging machine-learning algorithms, localization techniques can adapt and learn from data patterns, enabling more accurate and adaptive positioning. Artificial intelligence techniques can aid in making intelligent decisions and optimizing the localization processes based on real-time environmental information. Additionally, data fusion techniques that integrate information from various sources, such as sensor, environmental, and historical localization data, can improve the accuracy and reliability of WSN localization [156]. The integration of these technologies offers opportunities to address challenges, such as ranging errors, dynamic environments, and scalability, ultimately leading to more advanced and effective WSN localization solutions.

6) HANDLING HETEROGENEOUS NETWORKS: WSNs often comprise nodes with diverse capabilities, including variations in the sensing range, transmission power, and processing capabilities [72]. The development of localization techniques that can effectively handle heterogeneity and adapt to varying node characteristics is a significant research direction [157]. This involves designing algorithms that can account for and utilize the heterogeneous capabilities of nodes to optimize localization accuracy and energy efficiency. Techniques such as adaptive range estimation, dynamic power control, and node classification can be explored to address heterogeneity challenges in WSN localization. Additionally, considering node heterogeneity in the design of communication protocols, localization algorithms can help optimize resource allocation and improve the overall network performance.

7) STANDARDIZATION AND BENCHMARKING: Standardization and benchmarking play crucial roles in advancing WSN localization techniques. Establishing standardized evaluation metrics, datasets, and benchmarks enables fair comparison between different localization methods [103], [104]. It allows researchers to objectively assess the performance of their techniques and facilitates the identification of strengths and weaknesses. Standardized evaluation frameworks can include metrics, such as localization accuracy, energy consumption, computational complexity, localization time, and scalability [151]. The creation of standardized datasets that represent real-world scenarios and challenges enables researchers to validate and compare their algorithms under consistent conditions. Furthermore, developing benchmarking platforms and competition encourages collaboration and stimulates innovation within the research community.

SDN technology can play a significant role in optimizing the localization process of WSNs [158], [159]. SDN enables the centralized control and management of network resources, allowing efficient coordination and configuration of the network. This centralized control facilitates the deployment of localization algorithms across the WSN, ensuring consistent and synchronized operations. In addition, SDN's dynamic network configuration capabilities enable on-demand changes in network parameters, topology, and routing paths, adapting to real-time localization requirements and environmental changes. SDN can optimize data routing and forwarding by leveraging traffic engineering capabilities, thereby improving the accuracy and efficiency of WSN localization. It also provides Quality of Service (QoS) provisioning, allowing for the prioritization of traffic and allocation of appropriate resources to ensure reliable and timely data transmission for localization purposes. SDN's programmable architecture of SDN empowers developers to customize and extend network functionality, thereby enabling the implementation of specialized localization algorithms tailored to specific WSN deployment requirements. Furthermore, SDN enhances network monitoring and analytics, provides real-time visibility into the network's performance, and facilitates proactive identification of localization-related issues. With its security and privacy enhancements, SDN strengthens the protection of the localization data and ensures the integrity and confidentiality of the localization process. SDN optimizes WSN localization by offering centralized control, dynamic configuration, traffic optimization, QoS provisioning, programmability, monitoring capabilities, and security enhancements. These benefits lead to improved accuracy, efficiency, scalability, and reliability in WSN localization, enabling better utilization of network resources and support for various localization algorithms and protocols.

As depicted in Figure 13, the SDN architecture comprises two essential components: a central SD-Controller and a network device known as SD-Switches. These SD-Switches establish connections with wireless devices, that is, WSN nodes, through access points (AP). The data exchange between these devices is facilitated by the OpenFlow protocol [151], which is responsible for handling data transmission between network equipment and the SD-Controller, while also receiving updates from the SD-Controller. Consequently, this proposal offers an optimal solution for the placement of optimization algorithms, effectively addressing the problem at hand.

In terms of handling heterogeneous networks, SDN allows for flexible management of different node capabilities, such as varying sensing ranges, transmission powers, and processing capabilities. The SD-Controller can dynamically adapt and configure the behavior of SD-Switches based on the characteristics of individual nodes, enabling customized localization techniques to be applied to different node types within the network. This adaptability ensures that localization algorithms can effectively handle heterogeneity

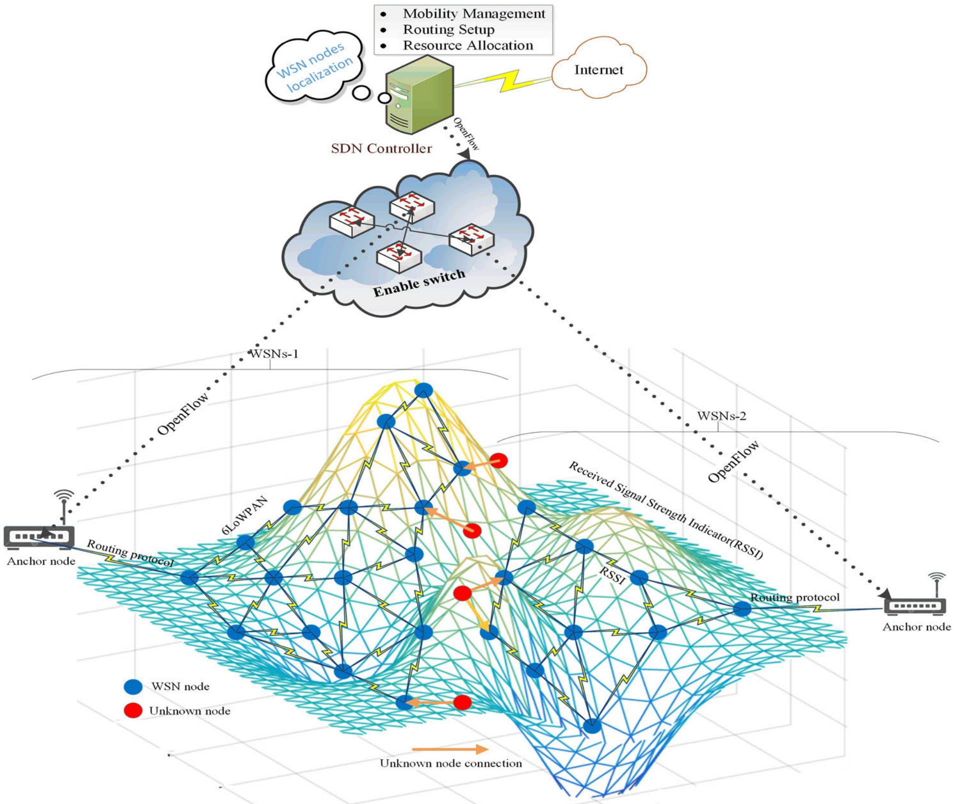

FIGURE 13. SDN architecture in implementation of WSNs nodes localization.

and cater to the diverse capabilities of the WSN nodes. Moreover, SDN can contribute to the integration of multiple technologies. With SDN, the SD-controller can facilitate the seamless integration of optimization algorithms with other technologies such as machine learning, artificial intelligence, or data fusion techniques. The centralized control provided by SDN architecture enables efficient coordination and collaboration between different technologies, leading to improved localization performance and robustness. By leveraging the capabilities of multiple technologies, WSN localization can benefit from enhanced accuracy, adaptability, and resilience under various environmental conditions. SDN offers scalable solutions by providing centralized management and control of the network. The SD-Controller can efficiently handle a large number of nodes, ensuring accurate localization while minimizing computational complexity. SDN's ability of SDN to dynamically allocate network resources and optimize routing decisions can contribute to achieving scalability in WSN localization, enabling the accurate positioning of a large-scale deployment without compromising performance. Moreover, SDN's centralized control and management enables it to handle dynamic environments effectively. The SD-controller can adapt to localization techniques based on real-time changes in network topology, node mobility, and varying signal propagation conditions. This adaptability allows for quick adjustments and optimizations in response to dynamic environmental factors, ensuring reliable and accurate localization results, even in rapidly changing scenarios.

Furthermore, the utilization of machine learning and artificial intelligence techniques can be instrumental in addressing the challenges associated with optimization. By employing intelligent algorithms, machine learning can dynamically enhance localization processes, draw insights from previous experience, and adjust to varying environmental conditions. Consequently, this can lead to notable improvements in the accuracy and efficiency of the WSN localization. Additionally, leveraging SDN within each segment area allows for the offloading of training and parameter tuning costs to the SD-controller, further optimizing the localization process.

VII. CONCLUSION

The accurate localization of sensor nodes is essential for the effective operation of WSNs. Achieving accurate WSN node localization is challenging owing to the wireless communication characteristics and dynamic nature of the network environment. Optimization algorithms have emerged as a promising approach to address this challenge. This review provides a comprehensive overview of WSN node localization and the application of optimization algorithms. We discussed various localization techniques and reviewed a diverse range of optimization techniques, including evolutionary algorithms, swarm intelligence, metaheuristic approaches, and other optimization-based methods. In addition, we evaluated and compared different optimization algorithms, considering factors such as accuracy, scalability, computational complexity, and robustness. Moreover, the proposed solutions focus on developing tailored optimization algorithms, incorporating the SDN technique, and leveraging machine learning for adaptive optimization.

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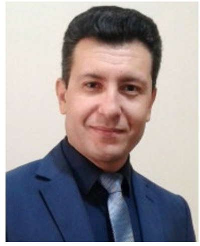

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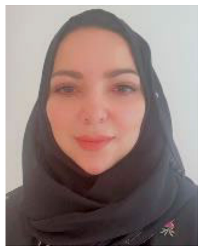

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