Wireless Personal Communications
https://doi.org/10.1007/s11277-023-10630-x

Unveiling the Cutting Edge: A Comprehensive Survey of Localization Techniques in WSN, Leveraging Optimization and Machine Learning Approaches

Preeti Yadav[1,2] · S. C. Sharma[1]

Accepted: 12 July 2023

Abstract

Sensor node localization is an important feature of many applications, including wireless sensor networks and location-based services. The accurate localization of sensor nodes improves system performance and reliability. This research emphasizes the benefits of using hybrid machine learning and optimization strategies for sensor node localization. Machine Learning (ML) algorithms, such as neural networks and support vector machines, are used to simulate complex correlations between sensor readings and related locations. These models enable precise prediction of node placements based on received signal strength, time of arrival, or other sensory inputs. The survey conducted in this study aims to uncover the latest advancements in localization strategies within Wireless Sensor Networks through the utilization of ML and Optimization Techniques. By thoroughly examining the existing literature, research gaps have been identified when localization techniques are solely employed. To provide a comprehensive understanding, this survey offers a detailed classification of localization algorithms, covering various aspects. Furthermore, the paper elaborates on the implementation of Optimization and Machine Learning approaches, exploring potential combinations with localization techniques. Through the use of analytical tables, the survey presents a comprehensive overview of sensor node localization using ML and optimized approaches. Additionally, the study addresses the challenges encountered and identifies potential future directions for the integration of these techniques.

Keywords WSN · Localization · Machine learning · Optimization techniques · ML based optimized localization

✉ Preeti Yadav
p_yadav1@pt.iitr.ac.in

[1] Electronics and Computer Discipline, IIT Roorkee, Roorkee, India

[2] Department of CSIT, M.J.P. Rohilkhand University, Bareilly, India

Published online: 29 September 2023

1 Introduction

A WSN is a collection of sensor nodes, scattered in distinct environments to monitor the activities and data storage. The acquired data is sent to a central place for further processing and analysis [1]. It is critical to accurately detect the placements of sensor nodes for WSNs to function properly by localization. Localization is essential in applications such as network management, object detection, and routing. Traditional techniques for localization in WSNs have primarily relied on either "range-based" or "range-free" methods. Range-based methods involve utilizing measurements of signal propagation characteristics such as "time of arrival" (ToA), "time difference of arrival" (TDoA), or "received signal strength" RSS to estimate distances between nodes. Conversely, range-free methods leverage network connectivity information and geometric relationships between nodes for localization. Despite their advancements, these techniques suffer from challenges such as signal attenuation, multipath effects, and environmental variations, leading to potential inaccuracies [2].

To overcome these challenges and enhance localization accuracy in WSNs, researchers have turned their attention to the integration of machine learning and optimization techniques. Machine learning algorithms offer the ability to extract patterns and relationships from extensive datasets, thereby improving localization accuracy. Machine learning algorithms can learn to provide precise predictions of node locations based on multiple input features by training models on vast volumes of sensor data [3].

Complementing machine learning, optimization techniques aim to find the optimal set of node positions that minimize localization errors. These techniques involve formulating an objective function that quantifies the discrepancy between estimated and actual positions and then optimizing this function using mathematical optimization algorithms. Through iterative adjustments to node positions, optimization techniques strive to converge toward an optimal solution that minimizes localization errors [4].

The fusion of machine learning and optimization techniques presents a promising approach for addressing localization challenges in WSNs. By integrating machine learning algorithms into the localization process, the system can learn from past observations, adapt to changing environmental conditions, and continually improve accuracy. Moreover, optimization techniques facilitate the refinement of node positions, by considering the facts like connectivity among nodes, energy efficiency, and reduced cost [5].

The integration of ML and OT for localization in WSNs is the focus of the study and analysis. We explore ML techniques K-nearest neighbor, decision tree, ensembled learning, manifold learning, etc., and assess their performance in terms of localization accuracy, error, communication cost, scalability, robustness, the environment, the areas of scenarios, and their outcomes. Additionally, we also analyzed the impact of implementing these ML techniques with optimization algorithms. We may overcome the limits of standard localization approaches and unlock the full potential of WSNs across multiple application areas by leveraging the capabilities of these new techniques [6]. Unconstrained optimization problems can be considered localization challenges. The optimization.

1.1 Motivation and Inspirations

The RSSI is widely used as a non-hardware solution for node localization. Sometimes this technique is not able to perform localization as per specified standards. Applying particle swarm optimization (PSO) to localization algorithms, the placement accuracy of RSSI increases [7].

Classical machine learning approaches paired with deep learning methods using Channel State Information (CSI) provide an aid to raise the performance. The proposed algorithms based on ML techniques are evaluated according to generalized properties for diverse phenomena and are evident as the best-performing techniques because it has the ability to be generalized. Deep learning models' generalization capacity can be improved so that they can learn the related aspects [8].

The most challenging aspect of indoor localization is it's constantly changing environment. It is often necessary to develop an IoT environment to tackle this difficulty. The preprocessing step is studied before the localization procedure to test the surroundings. The process of localization begins with identifying the moving dynamic nodes. The ML algorithms maintain a database of fingerprint map classification easily and efficiently. Deep Learning was shown to be the best appropriate technique in the proposed case [9].

Authors in [10] proposed a strategy to obtain outstanding results in indoor scenarios for localization. The proposed work is based on a Wi-Fi fingerprint. This method combines SISAE and RNN. To finish the localization process, the proposed techniques have been merged with an ML technique named logistic regression. It computes the location coordinates of the sensor nodes by improving accuracy.

Authors in [11] combined Deep learning patterns are combined with sensor observation and feeble classifiers to enhance the capabilities of localization algorithms. Due to Non-line of sight, the robots used to get unable in detecting their targets. It is obvious that the robot must be located for the robot system to be legitimate. To address the issue of lost localization, a deep learning technique supports the robot in generating exact patterns. CNN and RNN are applied to improve robot localization.

The issue of node aggregation and uneven placement of nodes may arise throughout the node deployment procedure. As a result, the need to create methods to reconfigure the described problem with the purpose of improving accuracy is being developed. These ways allow t to fix issues with the installation of sensor nodes in WSN [12].

1.2 Contribution to the Survey

Precision and efficient localization systems have been built by using the capabilities of machine learning algorithms. These technologies have had a significant impact on industries like autonomous vehicles, robots, and augmented reality. Machine learning models successfully analyze sensor data, such as GPS signals and visual inputs, allowing for real-time and accurate location identification of objects or devices. Furthermore, optimization approaches are important in refining localization algorithms, increasing accuracy while decreasing computing costs. The combination of machine learning and optimization enhances not just localization precision but also prepares the path for sophisticated applications such as intelligent navigation, personalized services, and seamless integration of virtual and physical realms. The integration of machine learning and optimization approaches in localization will continue to drive technical improvements, changing the future across multiple through continual research and development. According to the debate, the article has the following key contributions:

- The survey reveals the cutting edge by conducting a thorough examination of localization strategies in WSNs using ML and optimization approaches.

- Research gaps have been identified when localization techniques are implemented as sole for localization
- This survey provides a thorough classification of localization algorithms in every possible aspect.
- Optimization and Machine Learning approaches with possible combinations have been elaborated to implement them with localization techniques.
- An analytical survey through tables using machine learning and optimized approaches for sensor node localization is provided.
- Identified the challenges and future aspects of implementing the stated techniques together.

1.3 Broad Roadmap and Organization of the Article

This article follows a clear roadmap to explore the application of ML and optimization techniques in WSN localization. The introduction section sets the stage by highlighting the significance of this research and its relevance to current needs. The background and related work section provides a comprehensive overview of WSNs, localization techniques, OT, and ML in WSN. Section 2 identifies various research gaps and limitations of current approaches, paving the way for the proposed work. The background detail section i.e., Sect. 3 outlines the innovative schemes, and classifications of localization techniques, various ML and optimization approaches, the key components, and various employed algorithms in this regard. The analytical discussion Sect. 4 interprets and compares the existing approaches with flaws and highlights the strengths and identifies various challenges for implementing localization, ML, and optimization techniques together in Sect. 5. The conclusion Sect. 6 summarizes the findings and emphasizes the contributions and Sect. 6 calls for further research and implementation. Finally, the references section provides a comprehensive list of all cited sources, ensuring the credibility and validity of the article's content. Figure 1 is the pictorial representation of the roadmap of the article.

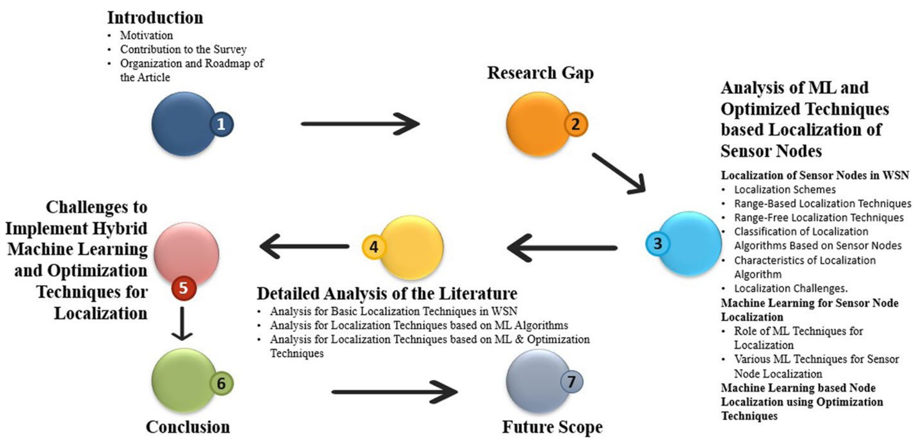


Fig. 1 Roadmap of the Article

2 Research Gaps

Localization entails calculating the spatial coordinates of sensor nodes within the network, which is critical in environmental monitoring, object tracking, target recognition, etc. The research landscape has seen a plethora of proposed localization strategies, including range-based methods based on the strength of the signal or time-of-flight measurement, and range-free alternatives based on connection and topology information. Despite significant progress, persistent difficulties and research gaps persist. These limitations include challenges with precision, energy efficiency, scalability, robustness in dynamic situations, integration with developing technologies, and the capacity to manage a wide range of deployment scenarios. The identification of these research gaps is critical because it guides future research, fosters innovation, and allows for the development of more effective and practical localization solutions capable of addressing the changing demands of WSN applications. A thorough assessment of existing research reveals where knowledge is inadequate, where inconsistencies or contradictions occur, and where additional research is required. In WSN localization, the following research gaps exist:

2.1 Finding the Precise Coordinates of the Sensor Nodes

While numerous strategies for localization have been presented, achieving high accuracy and precision remains a difficulty. Existing approaches may be limited by signal interference, non-line-of-sight circumstances, or barriers that make precise distance measurements impossible. Furthermore, the scalability of localization approaches in large-scale WSN deployments needs to be investigated further. Considerations for energy efficiency are also critical energy-efficient data transmission [13–15]. Furthermore, the stability of localization systems in dynamic situations where sensor nodes can move or undergo topological changes necessitates further investigation. Addressing these research gaps is critical for developing new algorithms and methods capable of finding sensor nodes in WSNs reliably and precisely. Such developments would considerably improve the network's data analysis, monitoring, and decision-making processes [16].

2.2 Recognizing the Sensor Nodes in Slumber Mode

Sleep mode is widely used to reduce energy consumption and extend the network lifetime by temporarily shutting specific nodes and lowering power consumption. However, establishing the presence and placement of sensor nodes in sleep mode remains difficult. Current approaches often rely on periodic wake-up cycles or pre-determined timetables, which may not adapt effectively to changing network circumstances or event patterns. It is critical to develop robust and efficient approaches for the real-time identification of sleeping nodes, especially in large-scale WSN deployments. Overcoming this research gap would allow for better energy management, more efficient data collecting, and overall network performance improvements in WSNs [17].

2.3 Converting the Relative Coordinates of the Sensor Nodes into Absolute

While relative localization methods provide information on node positions relative to each other, finding their absolute coordinates in a global reference frame remains difficult. Existing techniques frequently rely on a subset of anchor nodes with known positions or require external infrastructure for positioning. It is critical to develop strong and precise methods for converting relative coordinates into absolute positions without the use of additional infrastructure. Addressing this research gap will improve the precision and applicability of WSNs, allowing for more accurate location-based services, tracking, and monitoring across a variety of applications.

2.4 Clustering of Large Observing Regions

When the network spans large areas, efficiently splitting the monitoring zones into clusters becomes difficult. Due to issues such as communication overhead, energy consumption, and scalability, existing clustering algorithms may struggle to handle large-scale networks. Addressing this research gap will enable greater data aggregation, efficient resource allocation, and network performance, allowing WSNs to monitor and analyze large areas across several applications.

2.5 Mobility in Sensor Nodes

Unlike traditional WSNs, which assume fixed node placements, integrating node mobility presents new difficulties and opportunities. In the context of mobile nodes, factors like energy consumption, network connectivity, localization accuracy, and data routing must be addressed. It is critical to develop efficient protocols and algorithms that can adjust to node mobility patterns and ensure network connectivity. Furthermore, to improve WSN performance in dynamic situations, it is vital to investigate the impact of node mobility on data gathering, event detection, and resource management. Bridging this research gap will help to produce strong and dependable WSN solutions capable of operating well in real-world environments with mobile sensor nodes.

2.6 Classifying the Network Among Anchor and Non-anchor Nodes

It is critical in WSNs correctly identify the location of the nodes and classified as anchor or non-anchor. Existing classification algorithms frequently rely on established criteria or roles, which may not be flexible enough to deal with dynamic network conditions. Hence, it is needed to design resilient and adaptive algorithms to categorize nodes based on their capabilities, position, or role in the network. Addressing this research gap would improve network management, optimize resource allocation, and boost overall WSN performance, allowing for more effective data gathering, routing, and coordination between an anchor and non-anchor nodes.

2.7 Make the Maximized Utilization of Available Resources

Utilizing limited resources like energy, bandwidth, storage, and computing power efficiently is critical for optimizing WSN performance and longevity. Existing resource allocation and management strategies may underutilize existing resources or fail to adapt to changing network conditions. As a result, unique algorithms and strategies for intelligently allocating and distributing resources based on network requirements and limits are required. Closing this research gap would result in better resource utilization, increased network efficiency, and longer WSN operation, allowing resource-constrained applications to run more efficiently.

2.8 Implementation of Deep Learning Techniques for Localization of Sensor Nodes

While several methods for localization have been presented, the use of deep learning algorithms in this context is yet relatively unexplored. Deep learning models that can effectively exploit sensor data to properly estimate node placements are required to be developed and implemented. Closing this research gap would enable advanced and intelligent localization approaches in WSNs, allowing for greater spatial awareness and precise node location in a variety of applications.

2.9 Hybrid ML Techniques for Sensor Node Localization

Hybrid techniques in machine learning combine diverse algorithms such as deep learning, support vector machines, or ensemble methods. They are used for performance enhancement. It is critical to develop and implement hybrid ML models that successfully integrate information from disparate data sources and use the benefits of various algorithms. Addressing this research gap will result in more advanced and precise localization solutions in WSNs, increasing the precision and reliability of node positioning in a variety of application scenarios [18].

2.10 Implanting ML and Nature-Inspired Evolutionary Algorithm with Localization Techniques

While ML and evolutionary algorithms have been studied independently for localization, their combined use is relatively unknown. Deep learning and support vector machines, for example, can use data patterns to provide exact node locations, whereas evolutionary methods inspired by nature provide optimization capabilities. It is critical to creating hybrid models that mix ML and evolutionary methods for localization. Addressing this research gap would result in novel localization approaches that combine the benefits of ML and evolutionary algorithms, allowing for advanced and adaptive localization solutions in a variety of WSN applications.

2.11 Combining Hyper-Heuristics and ML Techniques with Localization Techniques

Hyper-heuristics give adaptive problem-solving methodologies, whilst machine learning techniques use data patterns to pinpoint node locations. The combination of these approaches has the potential to improve localization efficiency, accuracy, and adaptability in WSNs. An important step is to create hybrid models that integrate hyper-heuristics, ML approaches, and localization algorithms.

2.12 Robustness in Challenging Environments

Traditional localization approaches frequently fail in adverse situations including obstructions, signal interference, and NLOS conditions. There exists a substantial research gap in developing strong localization algorithms capable of dealing with such conditions. This research gap needs the investigation of approaches capable of mitigating the negative effects of external factors on localization accuracy, such as multipath effects, signal attenuation, and dynamic impediments.

2.13 Localization and Efficient Energy Transmission Trade-offs

Localization in WSNs often requires sensor nodes to expend additional energy for range measurements, signal processing, and communication. Finding a happy medium between energy consumption and localization accuracy is a significant scientific challenge. It is crucial to explore energy-efficient localization techniques that can minimize energy usage while still ensuring acceptable localization accuracy. This finding is especially important in resource-constrained WSNs where energy conservation is critical.

2.14 Privacy and Security

Localization information is frequently sensitive and prone to security risks, making it critical to preserve sensor node privacy while also ensuring the integrity and authenticity of localization data. Protecting these elements presents significant hurdles. As a result, it is critical to investigate research gaps in safe and privacy-preserving localization algorithms capable of ensuring authentication, secrecy, and integrity. It is critical to investigate and improve such strategies.

2.15 Fusion of Heterogeneous Localization Sources

Using several sources of localization information, such as GPS, landmarks, and anchor nodes, is crucial in performance improvement during node localization. The integration of data from disparate sources presents difficulties. Hence, there is a research need to create fusion systems that can harness the benefits of various localization sources while overcoming their limits.

The above identified research gaps provide directions to researchers to work in the extent of localizing the sensor nodes in WSN.

3 Analysis of ML and OT Based Localization of Sensor Nodes

Researchers can acquire insights into the effectiveness, performance, and trade-offs of OT and ML approaches for localizing a node by thoroughly analyzing and evaluating them. This research allows for the discovery of distinct methodologies' strengths, limitations, and prospective application domains. Researchers can contribute to the development of robust, precise, and efficient localization solutions in WSNs by identifying the most relevant strategies for various localization circumstances. This research project is critical in developing the field of WSN localization and promoting the use of more optimized and reliable localization systems.

3.1 Localizing the Sensor Nodes in WSN

The task of calculating the spatial coordinates of individual sensor nodes inside a WSN is termed sensor node localization. Precise node localization is essential for many applications, including object tracking, environmental monitoring, and target detection. Localization strategies are range-based methods that use signal strength or time-of-flight measurements and range-free methods that rely on connection and topology information. The idea behind localization is to precisely pinpoint the location of sensor nodes, allowing for more effective data collection, better routing, and node cooperation. Ongoing research is aimed at improving localization accuracy, scalability, energy efficiency, and adaptability to changing settings. These initiatives help to build more effective and practical localization solutions for WSNs [19]. Figure 2 shows how the localization process takes through the flowchart.

3.1.1 Localization Schemes

Localization schemes are techniques and algorithms used in WSNs precisely calculate or estimate the coordinates of the nodes. These techniques are critical for enabling a variety of WSN applications, including target tracking, environmental monitoring, and data fusion. They aid in accurate location by allowing for effective data collecting and coordination among sensor nodes. Figure 3 demonstrates various localization schemes and their techniques.

(a) Target/Source Localization

The process of calculating the precise coordinates or location of a specific target or source within a WSN is referred to as target/source localization. It entails properly determining the position of the target/source using measurements or data gathered by sensor nodes. Because of its unique properties or requirements, the target node is important in a variety of applications. Scenarios such as following the movement of an object, monitoring the position of a mobile node, or detecting a specific event or abnormality inside the network are examples of target node localization. This method provides accurate spatial information on the target node, allowing for targeted actions or analysis based on its location.

The process of finding the positions of source nodes inside WSN is known as source node localization. The method of source node localization allows for accurate mapping of these sensor node placements. This mapping is required for a variety of network management functions, such as routing, data fusion, and target tracking. The network can quickly route data, perform data fusion to acquire correct information, and monitor specific targets inside the network by properly understanding the positions of the source nodes.

These can be classified as single-Target/Source Localization and Multiple Target/Source Localization [20].

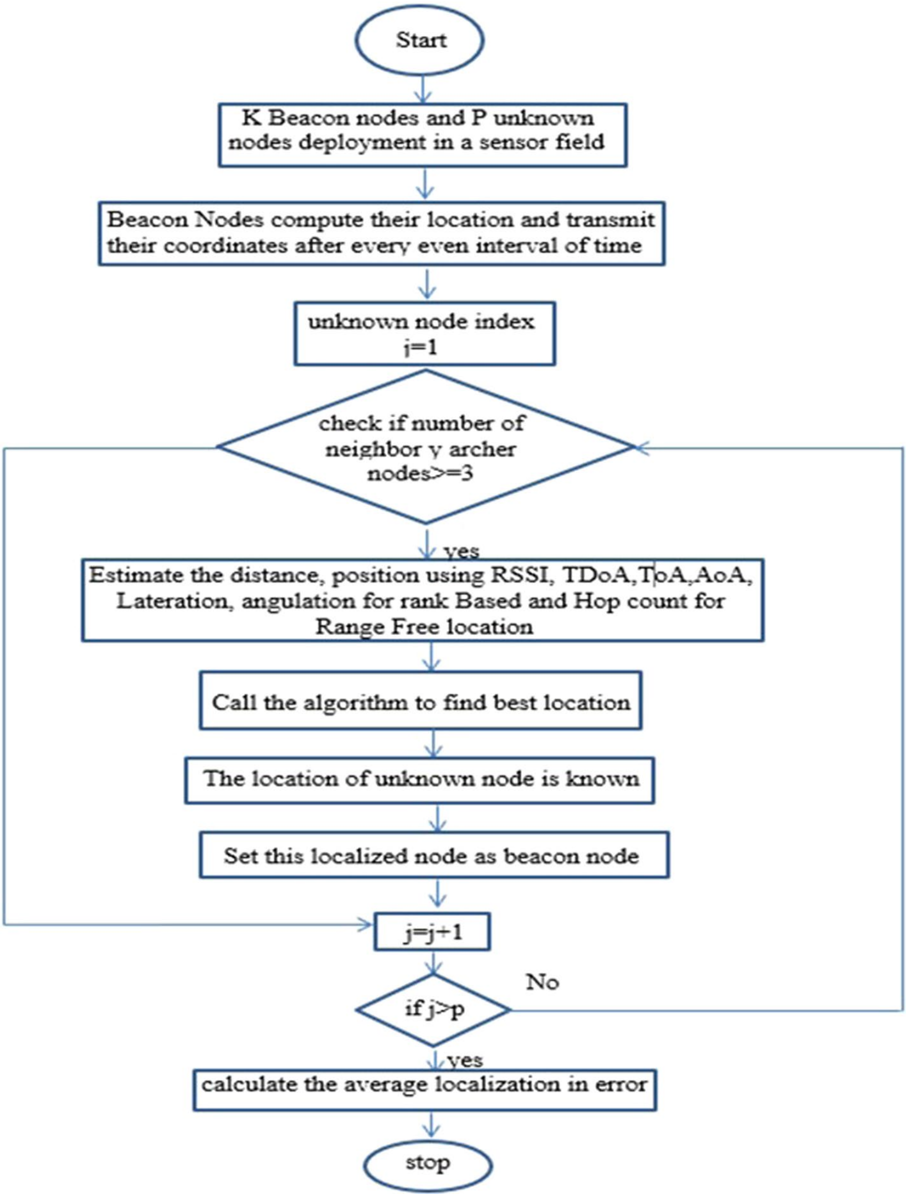


Fig. 2 Flowchart of Localization Process

The technique of precisely predicting the location or coordinates of a single source or target within a WSN is referred to as single source/target localization. It entails using sensor node readings or data to establish the precise position of the source/target. Object tracking, event localization, and point-of-interest monitoring are all applications of single source/target localization. The primary goal is to accurately localize a single

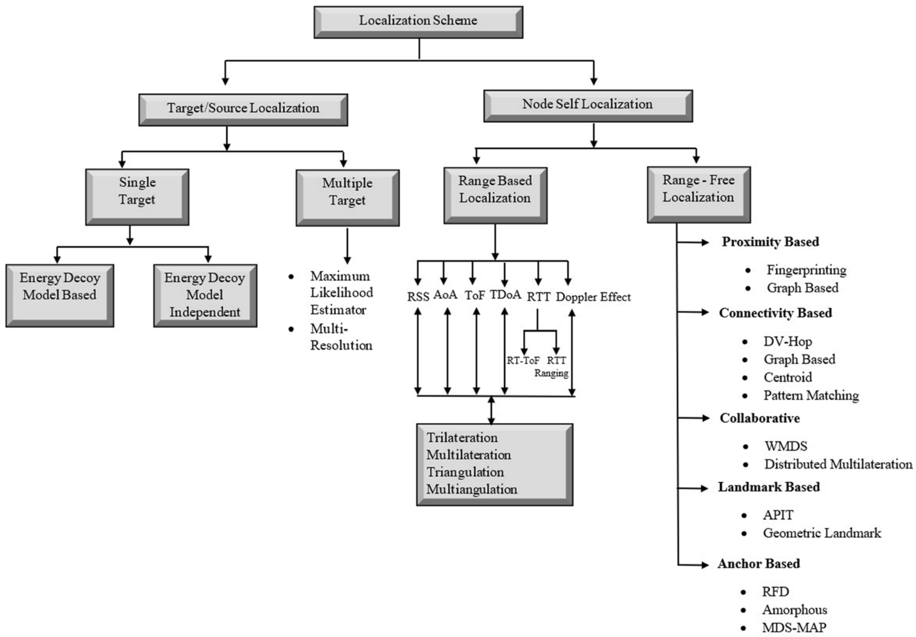


Fig. 3 Schemes for Sensor Node Localization

source/target, allowing for effective monitoring, tracking, or contact with the identified entity. There are two types of single-source localization algorithms:

- Model-based Localization Algorithms for Energy Decay
- Model Independent Localization Algorithms for Energy Decay

The simultaneous estimation of the locations of several sources or targets inside a WSN is termed multiple source/target localization. Many source/targets localization, as opposed to single target localization, which focuses on establishing the coordinates of a single entity, deals with localizing many entities at the same time. This scenario occurs in a variety of applications, including tracking numerous moving objects, monitoring multiple events, and localizing several signal or emission sources. The main problem is predicting the positions of many sources/targets properly utilizing measurements or data obtained from sensor nodes. This necessitates the creation of advanced localization algorithms capable of dealing with the difficulties of numerous simultaneous localizations. To accomplish precise and real-time localization of various sources/targets, these algorithms employ techniques such as data fusion, tracking algorithms, and estimate approaches. Advances in multiple source/target localization research aim to improve WSN capabilities in settings requiring simultaneous localization of many entities [21].

(b) Node Self Localization

The process by which individual nodes in a wireless sensor network (WSN) independently establish their positions without relying on external infrastructure or anchor nodes is known as node self-localization. Each sensor node estimates its position based on data gathered from its surroundings or interactions with neighboring nodes. Self-localization techniques are useful in situations when establishing a pre-existing infrastructure or relying on anchor nodes is prohibitive or impossible. These strategies are especially useful in ad hoc or mobile sensor networks, where nodes are dynamically placed or moved throughout the network.

There are numerous strategies for self-localization accessible, including range-based and range-free techniques. Range-based approaches evaluate a node's position concerning other nodes in the network by using distance or ranging data such as time of arrival (ToA) or received signal strength (RSS). Range-free approaches, on the other hand, use connection patterns, network structure, or geometric correlations between neighboring nodes to estimate a node's position.

Measurement inaccuracies, signal propagation variances, and environmental impediments all provide problems to self-localization. The focus of research efforts is on building efficient and accurate self-localization algorithms capable of addressing these issues and giving dependable position estimations for sensor nodes in the network. Broadly Node self-localization can be classified as:

- Range-based Localization Techniques
- Range-free Localization Techniques

3.1.2 Range-Based Techniques

They involve measuring the distances between sensor nodes to estimate their placements. To determine node-to-node distances, these algorithms use factors such as "received signal strength", "time-of-flight", "angle-of-arrival", or "time difference of arrival". Range-based localization methods that are regularly employed include trilateration, multi-lateration, and lateration [22]. Range-based localization techniques provide high accuracy by fulfilling line-of-sight conditions or with appropriate ranging equipment. They are, however, susceptible to some issues i.e. signal fluctuations, interference, and NLOS circumstances. The range-based techniques are classified as below:

(i) Received Signal Strength (RSS)

Distance estimation is the foundation for determining the position of every node in a sensor network [15]. The precision of distance measurement is determined by the strength of the received signal. The RSSI-based distance estimate technique necessitates the use of a signal propagation model. The most common model is the log-normal shadowing model. As the signal travels from source to destination, it weakens. Attenuation refers to the phase of receiving the signal. The value of attenuation is proportional to the distance traveled; the greater the distance traveled, the larger the value of attenuation. The strength of the signal can be utilized to calculate distance. The distance can be determined using the signal's transmitted power, received power, and the Path loss model. The power of the received signal $P_R^{ab}(\mathrm{t})$ transmitted by node a and received by node b at time t can be described using the following parameters as:

$$P_R^{ab}(\mathrm{t}) = P_T^a - 10\eta\log\left(d_{ab}\right) + X_{ab}(t) \tag{1}$$

η is the constant based on the attenuation of the signal, and d_{ab} is the distance a and b. $X_{ab}(\mathrm{t})$ is a variable whose value is affected by various environmental factors.

(ii) Time of Arrival (ToA)

The time of arrival (ToA) is an important parameter in WSNs for localization. It entails measuring or calculating the time it takes a signal from a certain transmitter or source to arrive at a receiving node. To identify the time difference between signal arrivals, ToA-based localization algorithms rely on exact time synchronization among sensor nodes. The distance between the source and receiving node can be estimated by knowing the speed of signal propagation. A sensor node can determine its own location by using distance measurements from numerous anchor nodes with known placements. To compute the distance, two types of measurements are used: One-way Arrival Time and Two-Way Arrival Time [23]. It necessitates close coordination between sender and recipient. The distance between two nodes is computed using the formula:

$$d_{ab} = (t_{sd} - t_{ds}) * v \tag{2}$$

d_{ab} is the distance between node a and b. The time ellipse in signal transmission and reception is t_{sd} and t_{ds}, and the signal propagation speed is v.

In two-way Time of Arrival, the receiver sends a data, which is promptly answered by a neighbor node, allowing the round-trip time between the two nodes to be calculated. The distance is computed as follows:

$$d_{ab} = \frac{(t_{sd_1} - t_{ds_1}) - (t_{sd} - t_{ds})}{2} * v \tag{3}$$

where d_{ab} is the distance between transmission and reception of a signal in Two-way Time of Arrival and t_{sd}, t_{ds}, t_{sd_1} and t_{ds_1} are the times of transmission and reception of the signal. This transmission is picturized in Fig. 4.

(iii) Time-of-Flight (ToF)

These techniques determine the distance by measuring the broadcast time of a signal during transmission among nodes. Typically accomplished by the use of radio waves or acoustic signals.

- *Radio Frequency Time of Flight (RF-ToF)* Estimates distance by measuring the broadcast time of a signal during transmission among nodes. Usually accomplished through the use of radio waves or acoustic signals.
- *Infrared Time of Flight (IR-ToF)* Estimates the distance by measuring the duration taking place as an infrared signal to travel between nodes. Frequently used in indoor positioning systems.

(iv) Time Difference of Arrival (TDoA)

To calculate time differences effectively, "TDoA-based" localization algorithms rely on exact time synchronization among sensor nodes. These time disparities can be turned into distance measurements by taking into account the speed of signal

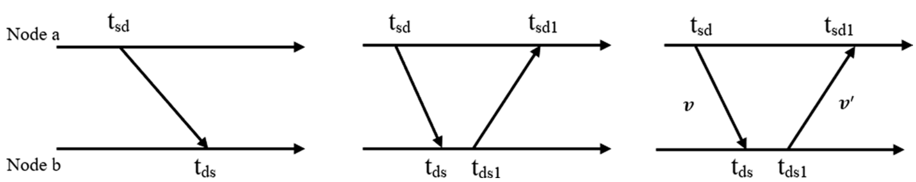


Fig. 4 Timing diagram of ToA [23]

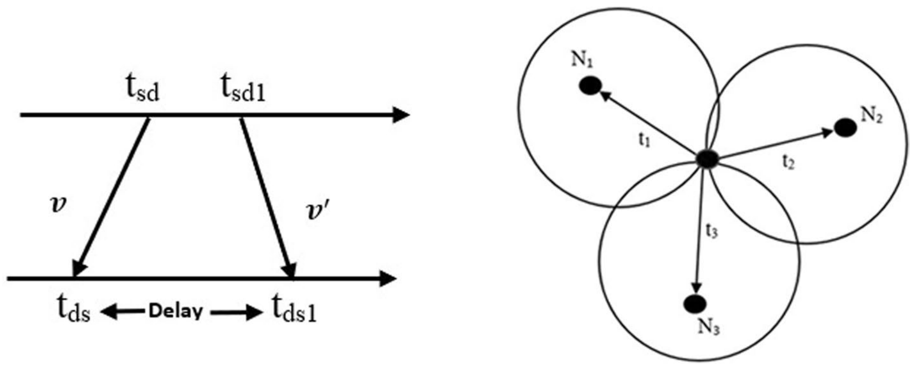


Fig. 5 TDoA for Multi-Signal and Multi-Node

propagation. It is classified as TDoA for Multi-signal and TDoA for Multi-node TDoA as shown in Fig. 5.

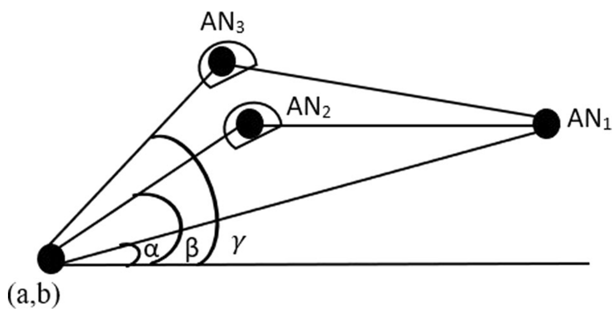
(v) Angle of Arrival (AoA)

Antenna arrays or directional antennas are used in AoA-based localization systems to measure or estimate these angles. The location of any node can be estimated by analyzing the angles of arrival from many anchor nodes with established placements. Localization based on AoA has the ability to offer precise and robust location data, especially in environments with clear line-of-sight conditions. To guarantee accurate and exact localization findings, difficulties such as signal reflections, interference, and calibration imperfections must be overcome. The combination of AoA readings and their locations aids in predicting the position of unknown node S. Figure 6 depicts the AoA Method's process. Here signal received from anchor nodes are used to locate node (a, b) by estimating the angle form all three anchor nodes as shown in Fig. 6.

(vi) Round-Trip Time (RTT)

RTT is the time, calculated by summing the time, when a signal moves from sender and receiver node and vice versa. This term is frequently used in acoustic-based localization systems. These algorithms assess the distance between nodes and identify their relative positions inside a WSN by analyzing the round-trip time. Here are two RTT-based localization techniques that are regularly used:

Fig. 6 Angle Measurement by AoA Technique



- *Round Trip Time of Flight (RT-ToF)* Monitoring the time it takes for a signal to go from a source node to a target node and then back to the source node is required for RT-ToF localization.
- *Round Trip Time-based Ranging (RTT Ranging)* RTT ranging attempts to precisely estimate the round trip time of a signal in bidirectional consideration. RTT ranging can make use of a variety of signal types, including radio waves and acoustic signals. Accurate measurement of time delays needs synchronized clocks between the source and target nodes.

Both RT-ToF and RTT ranging algorithms provide distance estimates based on signal round trip time. These techniques are often used in localization systems that require precise ranging information, such as indoor positioning, tracking, and navigation applications. They have advantages in terms of simplicity, cost-effectiveness, and interoperability with various communication systems. When using these techniques, however, restrictions such as signal propagation effects, ambient considerations, synchronization requirements, and accuracy loss over greater distances should be considered.

(vii) Doppler Effect

Estimates distance by using the frequency change in a signal induced by relative motion between nodes. When there is relative motion between a source sending a signal and an observer receiving the signal, the Doppler effect occurs. The signal's frequency appears to shift depending on whether the source and observer are travelling towards or away from each other. The received signal has a greater frequency (upshift) when the source and observer move closer together. When the source and observer move away from one other, the received signal has a lower frequency (downshift).

Localization based on the Doppler effect is used in scenarios that need precise velocity or distance data, such as object tracking, speed estimate, or collision avoidance systems. Its efficiency is notably noticeable in outdoor areas with clear routes between nodes, allowing for accurate Doppler measurements. However, it is critical to recognize that Doppler effect-based localization has several limits. Multipath interference, signal attenuation, and complex propagation settings can all jeopardize measurement accuracy and dependability. Furthermore, successful application of this technology frequently demands the use of specialized hardware and signal processing algorithms designed to extract meaningful information from frequency shifts.

The location is calculated based on Distance, angle and position of the nodes, Lateration and Angulation are the two basic techniques for performing range-based localization. They can also be divided into Trilateration, Multi-lateration, Triangulation, and Multi-angulation.

- *Trilateration* This approach is widely used in RSSI. To localize a node, at least three nodes with known locations must be present. Each circle in the diagram indicates the node's range, with the radius denoting the distance from the neighbor node. The juncture points of ranges creating three circles by the three nonlinear neighbors provides the precise location of the node.
- *Multi-lateration* Multi-lateration is a prominent technique that leverages timing delays in the arrival of numerous signals to pinpoint the exact position of an unknown node.

Trilateration does not deliver accurate results in a loud environment. To add distance metrics, we need more than three neighbor nodes. To localize the node, the difference between the measured and estimated distance is minimized in this case.

- *Triangulation* Triangulation is used mostly when angle information is required. In the AoA technique, the angle information provided by two anchor nodes is used to localize the node. The unknown node's position is calculated using basic trigonometry equations and angular measurements.
- *Multi-angulation* Multi-angulation is a localization technique used in WSNs to determine a sensor node's position. The angles of arrival of the signal from several nodes that know their location with known placements are measured. Multi-angulation determines the location by using trigonometric computations and angle measurements. This technique is especially useful when reliable angle-of-arrival data are available and line-of-sight conditions are favorable**.**

3.1.3 Range-Free Techniques

These techniques are widely used in WSNs to estimate sensor node placements without relying on precise distance measurements. In contrast to range-based methods, which require accurate distance information, range-free techniques use network connectivity and topology to infer node positions.

(i) Proximity-Based Techniques

Proximity-based approaches estimate node positions using proximity information like as signal strength (RSSI), angle of arrival (AoA), or proximity graphs. These methods use differences in signal characteristics to determine closeness or relative distance. RSSI-based Fingerprinting Techniques, Proximity Graph-based Localization, and AoA Localization are a few examples of these technique [24].

(ii) Connectivity-Based Techniques

Connectivity-based approaches estimate node placements by analyzing the network topology and the interactions between neighboring nodes. Centroid localization, DV-Hop, Connectivity-Based Localization (CBL), pattern matching, and Hop Count Localization are some examples of connectivity-based techniques.

(iii) Anchor-Based Techniques

Anchor-based approaches entail the usage of special nodes known as beacons in the network. These beacons broadcast their positions on a regular basis, and other nodes estimate their positions based on the beacon signals they receive. Range-Free Localization with Distance Estimation (RFD), Amorphous Localization, and MDS-MAP are a few examples.

(iv) Collaborative Localization

Collaborative localization approaches rely on network nodes cooperating to estimate their positions collectively. To increase localization accuracy, nodes exchange data and employ distributed algorithms. Distributed Multi-lateration, Weighted Multidimensional Scaling (WMDS), and Iterative Localization are three examples.

(v) Landmark-Based Techniques

Reference points or landmarks with established placements in the network are used in landmark-based approaches. Nodes calculate their positions by measuring the distances or angles between landmarks. APIT (Approximate Point-in-Triangle), Scene Analysis, and Geometric Landmark Placement are landmark-based techniques.

3.1.4 Sensor Nodes Based Classification for Localization Algorithms

Considering the above node localization schemes the localization criteria are further classified through the scenarios of sensor nodes [4].

- Algorithms that are Distribute and Centralized

  Individual sensor nodes estimate their positions autonomously by utilizing local measurements and interactions with neighboring nodes in distributed localization. This decentralized strategy eliminates the need for a central coordinator or infrastructure, allowing nodes to contribute to deciding their placements. In contrast, centralized localization involves a central entity, such as a base station or localization server, that collects readings from sensor nodes and performs the position estimation procedure. This centralized method offers the benefit of global information and controls over the localization process. However, it demands more communication and computational resources due to data flow between nodes and the central organization. The decision between distributed and centralized localization is influenced by several parameters, including network size, resource constraints, scalability requirements, and desired localization accuracy.
- Algorithms Inbuilt With GPS and Without GPS

  GPS-based localization is based on Global Positioning System (GPS) technology, in which sensor nodes receive signals from GPS satellites to correctly determine their positions. However, GPS-based localization is limited by GPS signal availability, which may be hindered or unavailable in some situations, such as indoors or underground locations. GPS-free localization approaches, on the other hand, do not rely on GPS signals and instead use alternative techniques.
- Algorithms With and Without Anchor Nodes

  A collection of anchor nodes with known positions is placed within the network for anchor-based localization. The other nodes' location is estimated by measurements among the anchors and themselves. Anchor-based localization algorithms commonly use trilateration or multi-lateration techniques.

  Anchor-free algorithms do not rely on specialized anchor nodes. Instead, they estimate their positions by leveraging sensor node connectivity and collaboration. These algorithms use network connectivity patterns, geometric features, or statistical inference methods to determine sensor node positions in the absence of external reference points.
- Algorithms for Stationary and Mobile Sensor Node

  Stationary sensor node algorithms are specifically intended for nodes that are fixed in place and do not move during network operation. Because stationary node positions remain constant throughout time, these algorithms are primarily concerned with optimizing localization accuracy and energy efficiency. They estimate node placements using range-based or range-free algorithms based on data collected from neighboring nodes or anchor nodes.

  In contrast, mobile sensor node algorithms are designed for nodes that can move across the network. These algorithms take node mobility into account and attempt to track and estimate their changing positions as they move. To constantly update the positions of mobile nodes, mobile node localization algorithms use techniques such as mobility prediction, trajectory modeling, or motion tracking. These algorithms

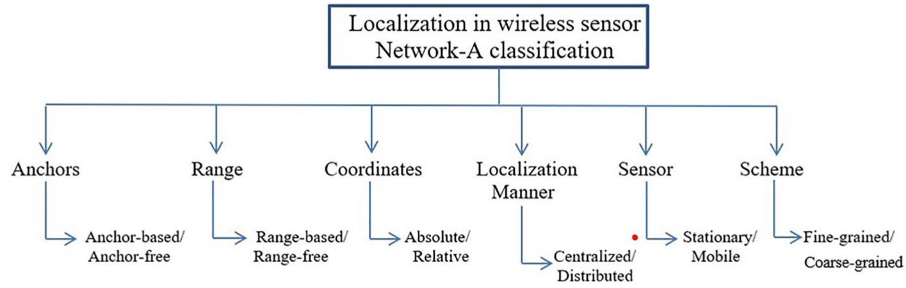


Fig. 7 Classification of Localization Algorithm

are crucial in applications that use mobile sensor nodes, such as environmental monitoring, surveillance, and robotics.

- Fine and Coarse Grained

  Individual sensor nodes execute localized data processing and aggregation in fine-grained algorithms, which work at a finer level of granularity. These algorithms allow for exact data control and analysis, resulting in more precision and detail. They may, however, necessitate greater computational resources and waste more energy. Coarse-grained algorithms, on the other hand, work with data gathering/processing handled by higher-level nodes or base stations. These algorithms combine data from several sensor nodes, lowering the quantity of data sent and the overall energy consumption. Coarse-grained algorithms are more scalable and energy efficient than fine-grained algorithms, although they may sacrifice some accuracy and control.

  The choice between fine-grained and coarse-grained algorithms is determined by the WSN application's specific requirements. Fine-grained algorithms are appropriate for applications requiring exact and detailed information, whereas coarse-grained algorithms are chosen for applications requiring scalability and energy efficiency.

- Relative and Absolute Coordinates

  Absolute node localization finds the precise spatial coordinates of nodes concerning a global reference frame. This is often accomplished through the use of systems such as GPS or anchor-based approaches that rely on external reference points. In contrast, relative node localization attempts to measure the positions of the nodes without using any external reference frame. This method infers relative positions by using metrics such as distance, angle, or connectivity information between neighboring nodes. Relative node localization gives useful information about the spatial relationships between nodes, which is especially beneficial when an absolute reference frame is unavailable or superfluous. Figures 7 and 8 represents these classifications in more specific manner.

3.1.5 Localization Algorithm Characteristics

Localization algorithm features in WSNs are governed by a variety of elements that shape their design and performance. These variables include infrastructure availability, network topology, node capabilities, localization needs, and deployment circumstances. The existing infrastructure influences the choice and feasibility of localization strategies [25]. Based on the above speech the localization algorithms have the following characteristics:

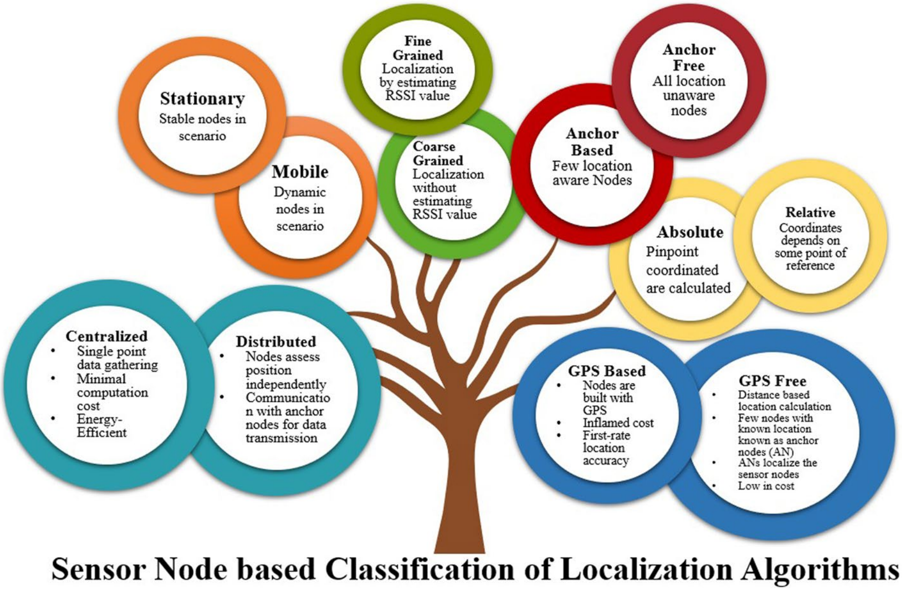


Fig. 8 Classification of Localization Algorithm

- *Robust to Environment* The algorithms for localization must be able to function in adverse settings. Robustness is an important feature of localization algorithms since it relates to their ability to deal with unfavorable situations and problems faced in WSNs. This includes problems like measurement mistakes, signal interference, ambient fluctuations, and obstructions. A robust localization method is resistant to noise, allowing it to offer accurate position estimations even in difficult situations. By overcoming these obstacles, robust algorithms ensure reliable localization results that are less sensitive to errors produced by outside cause [26].
- *Adaptive Nature* The accuracy of localization algorithms varies with anchor nodes. The more anchor nodes, the higher the precision. To adapt to changing network conditions and particular requirements, adaptive localization algorithms can dynamically adjust their parameters or behavior. These algorithms can efficiently adjust to node movement, signal fluctuations, and environmental changes, ensuring accurate and consistent position estimates throughout time. Adaptive localization algorithms optimize their performance by continuously modifying their operation to match the varying needs and problems faced in WSN. This adaptability increases their versatility and allows them to achieve consistent localization results throughout the network's operation [27].
- *Scalability* The localization process should not be influenced by changing count of sensor nodes. Scalability is a fundamental feature of localization algorithms that defines their ability to accept networks of various sizes. Scalable algorithms can quickly estimate node positions in small, medium, and large WSNs without sacrificing accuracy or computing cost. These algorithms can effectively scale their operations to manage different network sizes, delivering consistent and dependable localization performance regardless of network size. Scalable localization techniques demonstrate adaptability and suitability for various WSN installations by preserving efficiency and accuracy at varying scales.

- *RF-based algorithm* These methods use radio frequency waves to measure signal qualities in a non-intrusive and wireless manner. As a result, sensor nodes can be localized without extra infrastructure or physical contact. In localization, RF-based algorithms provide diversity and adaptability. They can be used in a variety of situations, including both indoor and outdoor settings, making them suited for a variety of deployment scenarios.
- *Depreciation in Response time* It refers to the reduction or minimization of the time required by a localization algorithm accurately measuring the location. Fast response times are critical, especially for applications that require real-time or near-real-time localization updates. Algorithms that deliver precise localization information quickly allow for prompt decision-making, efficient resource allocation, and effective coordination across sensor nodes. Furthermore, reducing response time contributes to energy efficiency by lowering overall communication and computing overhead in the network.
- *Accuracy* All localization methods must be as exact as possible in calculating node position. The accuracy of a localization algorithm is defined as the distance between the estimated and true positions of nodes. Accuracy is critical in many applications, particularly those that rely on accurate location information. Accurate localization simplifies tasks like target tracking, navigation, and location-based services. Accurate localization algorithms improve the dependability and efficacy of applications that rely on exact location information by reducing the difference between estimated and actual placements.
- *Consideration of Ad hoc Nature* These algorithms are specifically designed to operate in dynamic, self-organizing networks that do not rely on pre-existing infrastructure or centralized control. Because these algorithms are ad hoc, they may adapt and respond to changes in network conditions such as node failures, movement, and changes in network architecture. It enables the algorithms to offer WSN scalability by accommodating multiple deployment circumstances.
- *Universal Implementation* Localization techniques WSNs are distinguished by their universal implementation. It refers to an algorithm's ability to be built and utilized across many WSN deployments and scenarios without requiring significant alterations. A universally implemented localization technique can be used across multiple hardware platforms and network settings, providing versatility and adaptability. Because the same technique may be used in a variety of WSN applications and contexts, this feature simplifies the deployment and integration of localization solutions.
- *Energy Efficient and Energy Aware* Sensor nodes often operate on limited energy resources; energy efficiency is critical in WSNs. Hence, it is needed to prioritize energy efficiency to extend network operation and lifetime. Energy-efficient localization techniques are meant to reduce the energy consumption associated with position estimation, ensuring that available energy resources are used to their full potential. These algorithms contribute to network longevity, efficient resource allocation, and better network sustainability by minimizing energy use.
- *Deployment Flexibility* Certain localization methods are designed for certain deployment circumstances, while others are adaptable to parameters such as node distribution, node density, network structure, and ambient conditions. Flexible algorithms are adaptable and can be used in a variety of deployment scenarios, regardless of network parameters. These algorithms adapt to varied network setups and ambient variables, giving localization solutions that are usable in a variety of scenarios. Because they are flexible, such algorithms can successfully satisfy the localization needs of various wireless sensor network deployments.

- *Complexity* The computational and memory needs associated with a localization algorithm's execution determine its complexity. Lower complexity is more efficient and memory utilization, making them ideal for deployment in resource-constrained WSNs. These algorithms optimize resource utilization, allowing for efficient execution even with limited computing and memory resources. These methods provide effective localization while preserving optimal use of available resources in resource-constrained WSNs by minimizing complexity.
- *Communication Overhead* The volume of information exchange and message transmissions between nodes during the localization process is referred to as communication overhead. Localization algorithms with low communication overhead strive to reduce the number of messages transferred, lowering network congestion and energy usage. These algorithms optimize communication patterns and information transmission between nodes, ensuring efficient localization while minimizing the burden on network resources. These algorithms improve network performance, reduce energy consumption, and increase scalability in WSN by lowering communication overhead.

3.1.6 Localization Challenges

Localization offers many issues that must be solved to ensure precise and effective node positioning in WSNs. The specific characteristics of WSNs, such as limited computing and energy resources, communication limits, dynamic network circumstances, and environmental considerations, contribute to these issues [28]. Several issues are discussed below:

- *Efficient Energy Consumption in WSN Localization* One of the most critical concerns in network architecture is energy-efficient network infrastructure. The majority of the study is focused on energy-efficient localization. Nonetheless, dealing with it is a big task [29].
- *Anchor Nodes' Mobility* When anchor nodes move, their positions change over time, which can lead to mistakes in node localization. This complicates tracking the movements of anchor nodes and maintaining correct localization estimates. Overcoming this difficulty necessitates the development of localization algorithms that can successfully handle anchor node mobility, ensuring continuous and precise localization despite the dynamic nature of the anchor nodes [30].
- *Latency* Latency is the time taken during the localization of nodes while the sending and processing of data take place. Latency can affect the accuracy and timeliness of localization results in time-sensitive applications such as real-time tracking or monitoring. High latency can result in out-of-date or delayed location data, reducing the effectiveness of localization algorithms. Minimizing latency is critical for determining node placements quickly and accurately [31].
- *Adverse Environmental Effect* Adverse environmental circumstances present a substantial problem in localizing WSNs. Unfavorable phenomena such as signal interference, signal attenuation, and multipath effects can reduce the accuracy and reliability of localization algorithms. These ambient factors contribute to noise and distortions to the received signals, resulting in erroneous location predictions [32].
- *Reducing the Cost with Minimum Anchor node Placement* The cost of delivering and maintaining anchor nodes, which includes equipment, power usage, and installation labor, can be substantial. So, required to be reduced [33].

- *Inaccurate Coordinate Estimation or Measurement Error* Localization algorithms rely primarily on distance or proximity measurements, which are prone to errors generated by signal noise, interference, and measuring technique flaws. Addressing and minimizing these faults is critical for improving node localization accuracy. Error-mitigation strategies, such as robust filtering techniques, error modeling, and calibration procedures, are actively seeking to increase the reliability of distance measurements and reduce the negative impacts of measurement mistakes. Localization algorithms can provide more accurate and trustworthy estimations of node placements in the network by successfully correcting measurement inaccuracies [34].
- *Privacy and Security* Many algorithms gain better accuracy, but after implementation, they are vulnerable to numerous types of assaults. These assaults have an impact on the algorithm's performance. Localization algorithms face significant issues due to the confidentiality and privacy of localization information [35]. Because localization data might be sensitive, maintaining its security, integrity, and validity becomes critical. Safeguarding the privacy of sensor node locations and safeguarding against security threats are essential considerations. As a result, it is critical to implement significant security measures. The authors of [33] address several attacks for the same.
- *Localization in Mobile WSN* The dynamic nature of node movements complicates and uncertainly affects the localization process's accuracy and reliability. The shifting network topology, variable signal intensities, and unknown node positions make exact and real-time localization problematic in mobile WSNs.
- *3-Dimensional Setup* Unlike typical two-dimensional (2D) localization, finding the position of sensor nodes in a three- 3D space requires additional considerations and specialized methodologies. Complications like height, vertical distance, and multi-level situations must be handled. Localization algorithms must account for the vertical dimension and deal with issues such as signal attenuation, non-line-of-sight (NLOS) propagation, and 3D obstacles [36].
- *Error propagation* This is a big issue that must be addressed. Iterative localization algorithms are also implemented. As a result, there is a risk of the error spreading from one iteration to the next, ending in a significant problem.
- *Signal Propagation Variation* Addressing the impact of signal propagation variations is crucial to enhance performance. Localization algorithms are required to account for these variations and employ techniques to mitigate their adverse effects. This can involve the use of advanced signal processing algorithms, such as multipath mitigation techniques, channel modeling, or statistical approaches, to better estimate the true distance or proximity between nodes
- *Limited Resources* Research and development efforts are ongoing to develop resource-aware localization algorithms that can meet the unique requirements and limits of sensor nodes. Within WSN, these algorithms strive to optimize computational, memory, and energy utilization while assuring accurate position estimation.

The above-mentioned challenges are visualized in Fig. 9. Resolving these difficulties need ongoing research and development efforts. Machine learning and optimization techniques advancements can all contribute to the development of durable, secure, and efficient localization systems. To overcome these challenges, machine learning techniques may be efficiently employed for localization in WSN, enabling precise and trustworthy node positioning across a wide range of applications which will be discussed in the preceding sections.

Fig. 9 Challenges of Localization in WSN

3.2 Machine Learning for Sensor Node Localization

The use of machine learning methods for sensor node WSNs is a potential approach for addressing localization difficulties and improving accuracy. By leveraging machine learning capabilities, it is feasible to identify significant patterns and relationships from acquired data, enabling more robust and adaptive localization solutions. Machine learning algorithms may infer exact position information by analyzing numerous aspects such as signal characteristics, environmental circumstances, and sensor node behaviors. These algorithms can learn and improve over time with enhanced localization accuracy and reliability. The use of machine learning approaches in localization algorithms opens up possibilities for optimizing energy efficiency, dealing with changing network conditions and improving overall localization performance in WSNs. Figure 10 shows the possible application areas of WSN and the ML algorithms that can be applied on one of them i.e., localization.

3.2.1 Role of ML Techniques for Localization

The use of ML approaches in WSNs aids in the discovery of optimal solutions such as effective sensor node distribution, reduced complexity, and transmission bandwidth [21]. The use of ML approaches in localization has the following benefits:

(i) Classifying Sensor nodes from Anchor Nodes

After the ML model has demonstrated its efficiency, it can be used to categorize additional, unseen data instances. This integration into the WSN infrastructure provides automated node classification based on attributes or metrics.

(ii) Reduces the Need for Hardware

Machine learning approaches can use computer resources more efficiently and lower the computational complexity involved with localization. Machine learning

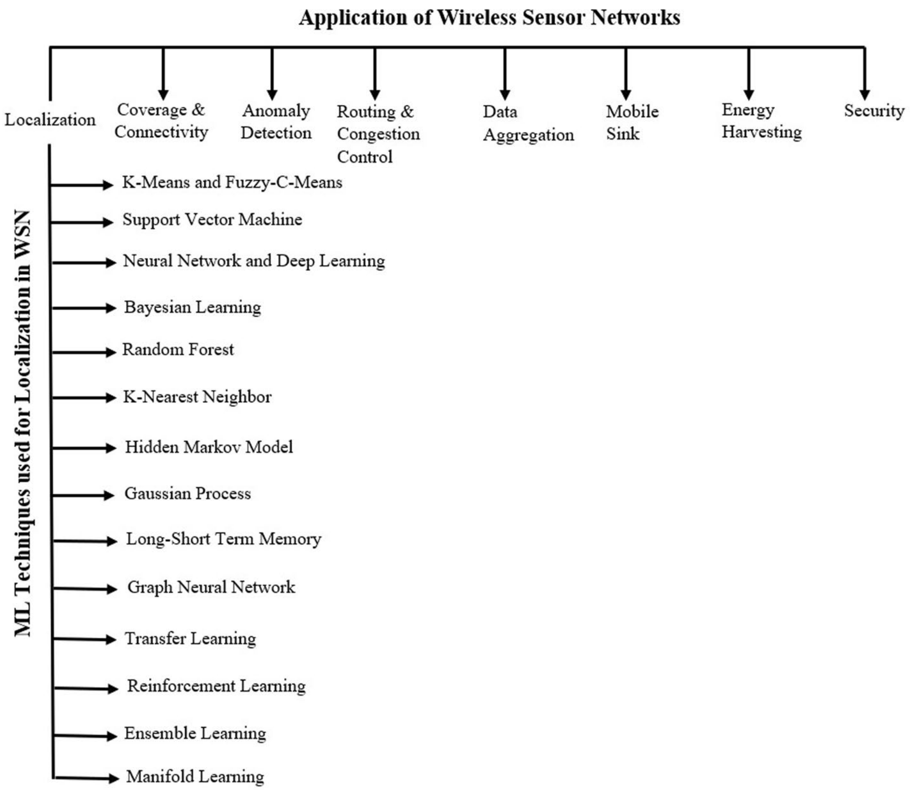


Fig. 10 Machine Learning Algorithms for Localization

models can produce exact localization results while minimizing computational needs by utilizing efficient algorithms and data processing techniques. This optimization of computing resources decreases the need for high-end hardware components and allows localization algorithms to be implemented on devices with limited resources. As a result, even in resource-constrained contexts, machine learning techniques provide a cost-effective and practical alternative to localization.

(iii) Improves the Localization Accuracy

Machine learning algorithms excel at learning patterns and relationships from large amounts of training data, resulting in improved node localization accuracy. Localization algorithms can efficiently handle limits and uncertainties associated with measurement data by utilizing machine learning, resulting in more precise and trustworthy position predictions.

(iv) For Dividing the Region into Custers

By taking into account the similarities and dissimilarities contained in the collected data, ML algorithms, notably clustering techniques, can be used to partition huge monitoring sites into clusters. This division allows for efficient monitoring of site organization, analysis, and management, allowing for targeted actions and informed decision-making processes.

(v) Robustness

The ability to handle noisy or faulty data is a significant advantage of applying machine learning techniques to localization systems. Machine learning approaches contribute to the generation of more trustworthy and robust position estimates by successfully coping with measurement errors, signal interference, and environmental fluctuations. This increased robustness is achieved by using machine learning models' capacity to capture complicated relationships and patterns in data. As a result, these models can efficiently correct for uncertainties, resulting in better localization system performance and accuracy.

(vi) Flexibility

Machine learning algorithms give flexibility by permitting the integration of multiple sources of information for localization. These strategies can combine data from numerous sensors, such as "signal strength", "time-of-flight", or "angle of arrival", to improve the accuracy of position estimation. Furthermore, ML models can adapt to diverse deployment circumstances, network topologies, and ambient variables, making them versatile for a wide range of localization applications.

(vii) Generalization to Unknown contexts

Machine learning algorithms can generalize learned patterns and models to unexpected contexts. These models can perform effectively in new, unknown contexts after being trained on a varied dataset. This generalization ability is useful in cases where the deployment environment may vary or change over time.

(viii) Improved Accuracy in Adverse Environments

Machine learning approaches flourish in complicated and challenging contexts where classic localization methods may struggle. For example, in situations with high noise levels, interference, or multipath propagation, machine learning algorithms can learn to filter out the noise and extract relevant data for more accurate localization.

(ix) For Real Time Localization

Machine learning algorithms can process data in real-time, allowing sensor nodes to be located immediately. This is especially useful in situations where instant or near-instant positional information is required, such as tracking moving objects or monitoring real-time events.

(x) Usage of Deep Learning (DL) Techniques to Conquer the Problems

DL techniques are able to cop up with the large amount of data generated during the localization process.

(xi) Reduced Energy Consumption

Machine learning techniques can optimize the localization process by minimizing the energy spent by sensor nodes. Machine learning models can lower energy requirements through effective data processing and transmission, extending the network's lifespan and conserving energy resources.

(xii) (xii) Multi-modal Localization

Machine learning approaches enable the merging of data from several sources, such as sensor readings, environmental information, or contextual data, to increase localization accuracy. Machine learning algorithms can capture supplementary data and give more reliable and exact position predictions by leveraging many sources of information.

(xiii) Adaptability

Machine learning algorithms are distinguished by their adaptability. This adaptability is especially useful in dynamic contexts where factors, such as node mobility or varied signal propagation characteristics, might change over time. Machine learning algorithms improve the accuracy and adaptability of the localization process by continuously updating and altering their models depending on fresh observations.

(xiv) Scalability

When used for large-scale WSNs, ML techniques provide a significant benefit in terms of scalability. These algorithms demonstrate effective processing and analysis skills for large volumes of data acquired from sensor nodes. As a result, machine learning allows for localization in networks with dense nodes or large coverage areas. Machine learning approaches, such as distributed learning or parallel computing, can be used to solve the computational demands of large-scale localization tasks. These strategies improve the scalability of the localization process while assuring effective computing resource utilization.

The above activities have been fetched based on the studies form [37–41]. Various machine learning algorithms have also been fused in next section that can be implemented with localization algorithms.

3.2.2 Various ML Techniques for Sensor Node Localization

To estimate the positions of sensor nodes in WSNs, machine learning techniques for node localization employ a variety of algorithms and methodologies. These strategies use labeled or unlabeled training data to learn patterns, relationships, or probabilistic models that aid in exact localization. Below mentioned are various machine learning techniques for sensor node localization and are pictorially represented in Fig. 11.

(i) K-Means or Fuzzy-C-Means

These are popular unsupervised machine-learning methods that allow sensor nodes to be grouped based on similarities in their measurements or attributes. These algorithms are critical in WSNs because they divide sensor nodes into discrete clusters, providing vital insights for localization and enabling further analysis or decision-making processes [42].

(ii) *Support Vector Machine (SVM)* It builds a classification model from labelled training data to distinguish between distinct classes or node positions. SVMs can accurately categorize nodes into their corresponding places or regions by training on labelled data [43].

(iii) *Neural Networks (NN) and Deep Learning (DL)* Based on the learned representations, these models learn spatial and temporal patterns from sensor data and create predictions. To accurately localize sensor nodes, neural networks must be trained on labeled data [44].

(iv) Bayesian Learning (BL)

There are various advantages of using Bayesian learning for node localization. It offers a versatile framework for incorporating past knowledge, which is especially valuable when training data is few. It also incorporates uncertainty into the localization process by providing a probabilistic representation of node placements. Bayesian learning is capable of handling complicated interactions and dependencies between sensor nodes and observed data, resulting in more accurate and robust localization outcomes [45].

(v) *Random Forest (RF)* Random Forests makes forecasts by mingling many decision trees. Random Forests can identify sensor nodes based on their features and attrib-

Fig. 11 Role of ML techniques in Localization

utes in the context of localization. Random Forests' ensemble nature allows them to capture complex linkages and improve node localization accuracy [46].

(vi) *K-Nearest Neighbor (KNN)* KNN is a basic but effective node localization algorithm. It classifies nodes based on the majority vote of their nearest neighbors. Because it is based on the proximity of data points, KNN does not require training. However, significant consideration must be given to the right value of K, the number of neighbors considered [47].

(vii) *Markov Model (HMM)* HMMs are sequential models used to locate nodes in dynamic situations. HMMs record temporal connections in sensor data and can estimate sensor node positions based on observed sequences [48].

(viii) Gaussian Processes (GP) Gaussian Processes are probabilistic models used for node localization. They simulate the spatial interactions between nodes and estimate the probability distribution over node positions. To make predictions about the placements of sensor nodes, GP-based localization uses Bayesian inference [49].

(ix) Long Short-Term Memory (LSTM) LSTM can effectively handle long-range dependencies in sequential data. LSTM models have been applied to node localization tasks where temporal information plays a crucial role, such as tracking or localization in mobile sensor networks. LSTM networks can capture complex temporal patterns and make accurate predictions based on historical data [50].

(x) *Graph Neural Networks (GNN)* GNNs are deep learning models that are specifically built to cope with graph-structured data, is a typical format for sensor networks. GNNs can learn about the spatial relationships between sensor nodes and use this information to help with localization. GNNs may incorporate neighborhood information and generate accurate predictions about sensor node placements by propagating information across the graph structure [51].

(xi) *Transfer Learning (TL)* In this technique, a pre-trained model, often learned on a large dataset, is fine-tuned or adapted to a specific localization job with little labeled data. Transfer learning enables more efficient and successful training of localization models by using knowledge obtained during the pre-training phase, particularly in cases when labeled training data is minimal [52].

(xii) *Reinforcement Learning (RL)* RL emphasizes on discovering optimum decision-making strategies through interactions with the environment. In dynamic and uncertain situations, RL approaches can be used for node localization. Based on input and rewards from the environment, RL algorithms can learn policies that decide the most suitable step to enhance localization accuracy [53].

(xiii) *Ensemble Learning (EL)* Ensemble learning predicts outcomes by merging many machine learning models. Ensemble learning can be used to increase the accuracy and durability of node localization models. Bagging, boosting, and stacking techniques can be used to integrate the predictions of many models, reducing the risk of overfitting and improving generalization performance [54].

(xiv) *Manifold Learning (ML)* Manifold learning can be used to identify the low-dimensional representation of sensor nodes based on their spatial relationships or closeness in node localization tasks. This technique makes use of the data's underlying structure to find clusters or groupings of nodes, which might be useful for localization. Manifold learning procedures give a condensed representation of the data by lowering its dimensionality, which may then be utilized as input for other machine learning algorithms or localization techniques to properly estimate the positions of the nodes [55].

Many real-world datasets include nonlinear relationships and rich geometric aspects that linear approaches like principal component analysis (PCA) cannot adequately represent. Many learning techniques are specifically designed to address this issue [56]. These techniques excel in handling nonlinear relationships within data, allowing them to produce a more precise and authentic depiction of the underlying structure. Researchers can obtain deeper insights into the complex patterns and relationships contained in data by using the power of manifold learning, which is especially useful for tasks such as data visualization, grouping, and understanding the intrinsic aspects of the dataset.

The ML techniques discussed above can be used in a variety of ways. These hybrid ML algorithms can possibly applied to increase accuracy while decreasing error in localizing the nodes. Many aspects of localization may be improved using hybrid machine learning, including communication cost, computation cost, accuracy, throughput, RTT, energy consumption, localization error, packet delivery rationing, and so on. These hybrid ML techniques combined with optimization techniques have the potential to significantly improve the aforementioned parameters. The next sub section explores the discussion made above.

3.3 Machine Learning Based Node Localization Using Optimization Techniques

The tremendous amount of data available now has become the most difficult problem. Finding the best answer for a data-driven problem is an exciting task. In such cases, optimization approaches come in handy [57]. Sensor node deployment in any environment has a substantial impact on the performance of any network. The location of sensor nodes impacts considerably on performance evaluation [58]. The criteria are also beneficial to the mobile sensor nodes. Optimization methods such as grey wolf are utilized for during path planning of these anchor nodes without any hindrance [59]. For optimal node localization, optimization techniques play a vital role to identify the anchor nodes that keep on participating in estimating the node location [60].

Researchers have made significant progress in improving the precision of node localization through amalgamating OT and ML strategies, which has opened up a plethora of possibilities for applications such as asset tracking, environmental monitoring, and location-based services for mobile devices. The continual advancement of optimization algorithms and ML models has the aspects for accurate and reliable node localization procedures, hence opening up new avenues for innovation across multiple fields.

Numerous publications demonstrate localization strategies applied with OT, localization algorithms with ML approaches, and ML with OT. However, there exists very little literature that incorporates all three strategies as shown in Table 1. Implementing the three strategies, namely localization, machine learning, and optimization have a few benefits:

(i) Particle Swarm Optimization (PSO)

When PSO is integrated with machine learning approaches for node localization, it can improve the accuracy, efficiency, and resilience of the process. Here are some ways in which PSO can help when used with other machine-learning techniques [61–64]:

- *PSO with Neural Networks* PSO can optimize the weights and biases of node localization neural network models. PSO helps neural networks converge to better solutions by searching the weight space, resulting in enhanced localization accuracy.
- *PSO with DL* PSO optimizes the parameters of deep learning models used for node localization, such as deep neural networks, CNNs, or RNNs. PSO assists in determining the ideal network weights and biases, leading to more accurate localization outcomes.
- *PSO with SVM* PSO can identify the optimal settings for node localization by exploring the SVM parameter space, which includes kernel parameters and regularisation parameters.

Table 1 Machine learning algorithms implemented with optimization algorithms for localization

Optimization techniques	K-Means Fuzzy-C-means	ANN	GA	SVM	SVR	NN/DL	DT	BL	RF	KNN	HMM	GP	RL	EL	ML	PCA	AdaBoost	SOM	ELM	GMM
PSO				✓		✓			✓			✓		✓						
BA							✓				✓						✓	✓	✓	✓
2-Hop MSA	✓	✓						✓												
BOA			✓									✓	✓				✓			
CSA					✓	✓														
OSEL					✓	✓				✓		✓		✓						
ABC							✓		✓											
Firefly		✓		✓					✓		✓	✓								
ACO		✓		✓							✓	✓				✓	✓	✓		
GWO		✓		✓				✓			✓							✓	✓	

- *PSO with Gaussian Processes (GP)* The hyperparameters of Gaussian Processes used for node localization can be optimized using PSO. The accuracy and versatility of GP-based localization can be increased by utilizing PSO to identify the ideal values of parameters such as length scales, noise levels, or covariance functions.
- *PSO with Random Forests* PSO can optimize random forest model hyperparameters for node localization, such as the number of trees, tree depth, and feature subset size. The performance of random forests in node localization can be improved by tweaking these hyperparameters using PSO.
- *PSO with Ensemble Learning* PSO can optimize the ensemble model combination weights used for node localization. PSO can improve the overall performance of the system by altering the weights allocated to each model within the ensemble.

(ii) Bat Algorithm (BA)

The Bat Optimisation Algorithm (BA) for node localization has rapid enhancement in the performance when applied with machine-learning approaches. This algorithm exceeds the performance of localization algorithms with improved performance. Here are some machine learning algorithms that can be implemented in conjunction with BA [65–69]:

- *BA with Hidden Markov Models (HMM)* HMMs are sequential models that can be used to locate nodes in dynamic situations. They estimate node positions by capturing temporal connections in sensor data. Localization accuracy can be improved by employing BA to optimize HMM parameters such as transition probabilities and emission probabilities.
- *BA with Decision Trees* Decision trees are commonly used for classification and regression applications, as well as node localization. Localization accuracy can be improved by utilizing BA to optimize the parameters of decision tree models such as tree depth and splitting criteria.
- *BA with K-Nearest Neighbours (KNN)* KNN is an effective node localization technique that classifies nodes based on the majority vote of their nearest neighbors. To increase localization accuracy, BA can optimize the value of K and other KNN hyperparameters.
- *BA with Adaptive Boosting (AdaBoost)* AdaBoost combines feeble classifiers for the formation of a more powerful classifier. When paired with BA, it can increase node localization performance by optimizing the weights provided to each weak classifier.
- *BA with Self-Organizing Maps (SOM)* BA can optimize SOM parameters such as node count and learning rate to improve sensor node organization and representation, leading to improved localization.
- *BA with Extreme Learning Machines (ELM)* The ELM is a fast-learning neural network algorithm containing a single hidden layer that performs well in generalisation. ELM's weights and biases can be optimised when paired with BA to improve node localization accuracy. This is especially useful for large-scale sensor networks.
- *BA with GMM* GMM is a probabilistic model that portrays data distribution as a mixture of Gaussian components. It can be used to group sensor nodes and estimate their positions. The Bat Optimization Algorithm (BA) can increase node localization accuracy by optimizing GMM parameters such as the number of components and the mean and covariance of each component.

(iii) 2-Hop Mass Spring Algorithm (2-Hop MSA)

In conjunction with the 2-hop mass-spring approach a number of ML can be employed for node localization. Among these algorithms are [70, 71]:

- *Artificial Neural Networks (ANN)* To establish the association between node attributes and their respective placements inside the 2-hop mass spring technique, "Artificial Neural Network (ANN)" models such as "Multilayer Perceptron (MLP)" can be used. By training the ANN model with labeled data, it gains the ability to forecast the placements of unlabelled nodes using the 2-hop connection information.
- *Bayesian Networks* Through probabilistic graphical models, Bayesian networks can express the interdependencies between node properties and their corresponding placements. Bayesian networks assist the estimate of node placements by utilizing their 2-hop connection and other observed properties by collecting the network structure and conditional probability distributions from training data.

(iv) Butterfly Optimization Algorithm (BOA)

Several ML approaches are used in combination with the Butterfly Optimization Algorithm for node localization. Some of these techniques include [72–76]:

- *Genetic Algorithm (GA)* To find optimal solutions, genetic algorithms can conduct population-based searches. When paired with the Butterfly Optimisation Algorithm, GA can optimize the parameters of machine learning models used for node localization, such as neural network weights and architectures or probabilistic model parameters.
- *Reinforcement Learning* Through interactions with the environment, RL algorithms, such as Q-learning or Policy Gradient techniques, can learn optimal policies for node localization. To increase localization performance, the Butterfly Optimisation Algorithm can be used to optimize RL parameters such as the exploration–exploitation trade-off or learning rates.
- *Gradient Boosting* Gradient boosting algorithms, such as XGBoost or LightGBM, can be used to build ensemble models for node localization that integrate many weak learners. To increase localization performance, the Butterfly Optimisation Algorithm can be used to optimize boosting parameters. These parameters may be the total count of estimators, learning rate, and so on.

(v) Cuckoo Search Algorithm (CSA)

This optimization tool is inspired by a bird named Cuckoo's breeding behavior. It is a metaheuristic method that may be coupled with machine learning techniques to identify optimal solutions for the parameters and structures of node localization machine learning models. The Cuckoo Search algorithm improves localization performance by effectively searching the search space, resulting in increased accuracy and effectiveness [72, 77–80].

- *Cuckoo Search with SVR* When Cuckoo Search is applied with SVR, it rapid and less error-prone prediction for location estimation.
- *Cuckoo Search with Neural Network* The scenario achieves very high accuracy when the cuckoo search is implemented with the neural network. It also provides a reliable platform for efficient data transmission.

(vi) Optimization-based Self-Localization (OSEL)

OSEL (Optimization-based Self-Localization) is an optimization technique that depends on RSS data for node localization. Although OSEL does not include machine-learning techniques, it can be integrated with specific machine-learning approaches to improve localization. Several machine learning algorithms for sensor node localization can be combined with OSEL:

- *Regression Models* To establish the association between RSS data and actual node placements, use regression models such as "linear regression", "support vector regression", or "neural networks". They can determine the placements of sensor nodes based on received signal intensity by training these algorithms with labeled data.
- *KNN* It is an effective localization ML technique. KNN can find the K data points to predict node placements based on their positions given a set of RSS measurements. By integrating the optimization process into the KNN-based estimation, the accuracy of localization can be improved by combining KNN with OSEL.
- *Gaussian Process Regression (GPR)* This ML technique may capture complex input–output correlations. A probabilistic model can be generated by training a GPR model with RSS measurements and related node positions. This model provides position estimations as well as confidence intervals. OSEL can be used to optimize the GPR model's hyper parameters or to refine the position estimates produced from GPR.
- *Ensemble Learning* By merging different machine learning models, ensemble learning approaches such as random forests or gradient boosting can increase localization accuracy. The diversity of the models and their collective predictions can be utilized to refine the localization results acquired through OSEL by training an ensemble of models utilizing RSS readings and associated positions.
- *Deep Learning* Deep learning methods can learn detailed patterns for node localization from RSS measurements. These models may be trained on large datasets to incorporate spatial dependencies and estimate node placements accurately. By incorporating OSEL into the training process or by utilizing OSEL to adjust the localization results produced from deep learning models one can get localization algorithms' results at very accurate level.

The optimization capabilities of OSEL can be integrated with the learning capabilities of machine learning by integrating OSEL with appropriate machine learning algorithms, improving the accuracy and resilience of sensor node localization.

(vii) Artificial Bee Colony (ABC)

When machine learning approaches are combined with ABC for node localization, the optimization process and accuracy are improved. The efficiency, accuracy, and robustness can be improved by integrating machine learning techniques into the ABC algorithm [81–83].

- *Reinforcement Learning* RL techniques, like Q-learning or deep reinforcement learning, can be applied to sensor node localization. Reinforcement learning agents learn to make sequential decisions to optimize node positions based on environmental feedback. ABC can optimize the exploration–exploitation trade-off or refine localization results obtained from reinforcement learning agents.
- *Decision Tree* When employing decision tree techniques for sensor node localization, decision trees can be trained using sensor node attributes and positions. This allows mapping between features and node positions to be established. To improve the localization process, the ABC technique can be used to optimize the decision tree parameters or refine the decision tree's localization findings. The combination

of ABC and decision trees have the potential to improve accuracy and performance in sensor node localization.

(viii) Teaching Learning Based Optimization Algorithm (TLBO)

"Teaching-Learning-Based Optimization" (TLBO) is a population-based optimization algorithm that can be utilized alongside ML algorithms to aid in the localization of sensor nodes. While TLBO is not inherently tied to machine learning algorithms, it can be integrated with them to enhance the localization process.

(ix) Firefly Algorithm (FA)

For optimization, FA simulates the flashing behavior of fireflies. Fireflies are drawn to brighter fireflies and gravitate towards them, guiding the optimization process. To optimize node placements inside the search space, FA has been used in node localization.

(x) Ant Colony Optimization (ACO)

ACO is essentially a search algorithm inspired by ant foraging behavior. ACO, on the other hand, can be combined with a variety of machine-learning techniques to improve sensor node localization. Here are a few ML methods that are widely used in conjunction with ACO to locate sensor nodes:

- *Adaptive Boosting (AdaBoost)* AdaBoost is a boosting technique that combines weak classifiers iteratively to build a strong classifier. ACO can be used in conjunction with AdaBoost to optimize the parameters and weights of weak classifiers, hence boosting sensor node localization accuracy.
- *Self-Organizing Maps (SOM)* SOM is a clustering and visualization algorithm that uses unsupervised learning. ACO can be used to optimize SOM parameters such as grid size and learning rate to improve the quality of the SOM representation for sensor node localization.
- *Principal Component Analysis (PCA)* PCA is a feature extraction technique for dimensionality reduction. ACO can be coupled with PCA to improve sensor node localization performance by optimizing the primary components and reducing data dimensionality.

(xi) Grey Wolf Optimization (GWO)

GWO is used as an optimization approach to fine-tune the machine learning model's parameters. This entails encoding the model parameters as the positions of the grey wolves and iteratively optimizing the model's performance using GWO's update rules.

4 Literature Analysis

In this section, an exhaustive analysis of various works of literature on WSN localization, ML in localization, and ML with optimization techniques for localization has been well-thought-out.

4.1 Analysis for Basic Localization Techniques in WSN

Table 2 analyses various localization strategies taking into account a variety of criteria such as localization technique, region, accuracy, computation time, and communication cost, according to the nature of anchor nodes and their patterns and density, and framework. This identifies the flaws when localization techniques are used in isolation. This analysis also entails the error estimation criteria in the discussed fragments of literature.

Authors in [84, 85] proposed range-based localization techniques on standard parameters. Authors in [86] proposed an approach for deploying sensor nodes efficiently. The devised approach extends the network lifetime while reducing energy usage and localization inaccuracy. The DV-Hop algorithm has a problem with extra node deployment in the same location, which can be solved by this work. The approach improves localization error, energy consumption, and accuracy.

Nemer et al. [33] investigated a variety of range-free localization approaches. They used MATLAB to simulate five range-free algorithms and compared their outcomes on various settings and topologies. Localization accuracy and energy usage are the characteristics against which algorithms are compared. The inaccuracy (accuracy) in position estimation can be calculated as:

$$Error = \frac{\sum_{i=1}^{n} \sqrt{(x_i - x_i')^2 + y_i - y_i')^2}}{NR} \tag{4}$$

here error is calculated by calculating the distance between nodes.

Sun et al. [87] presented a path planning approach (PP-MMAN) for moving anchor nodes with exceeded counts. The proposed strategy minimizes anchor node energy usage. It also shortens the route. The proposed solution saves energy in this during the broadcast of packets. The compensation algorithm for positioning is developed to address the issue of border nodes that are unable to determine their location owing to a lack of positional information. The ALE can be calculated as the difference between the actual and calculated location:

$$e = \frac{1}{n} \sum_{s=1}^{n} \sqrt{\left(x_s - \hat{x}_s\right)^2 + \left(y_s - \hat{y}_s\right)^2} \tag{5}$$

Kouroshnezhad et al. [88] suggested an optimal priority-based trajectory with energy constraint (OPTEC) movable anchor trajectory planning technique. The rate of ineffective beacon points (IBR) is calculated by dividing the number of effective beacon points by the total number of beacon points.

$$IBR = 1 - \frac{\#effective\ of\ beacon\ points}{total\ number\ of\ beacon\ points} \tag{6}$$

Alavijeh et al. [89] propose a relationship of distance and RSSI value. For the same EKF has been chosen to be outperforming. Conversion in EKF into a covariance matrix aids in accuracy. The simulation results reveal that the proposed VCEKF delivers 22% more accuracy than the CCEKF for static hidden nodes. RMSE can be calculated by the estimated and accurate location for N sensor nodes and k anchor nodes.

Table 2 Analysis for sensor node localization techniques and parameters in WSN

References	LA	RC	Dim	Accuracy	Scalable	Robust	CT	CC	AS	ANO	ES
Krishanmoorty et al. [84]	RSSI	RB	Low	Improved	No	No	Exceed	Susceed	Still	Continual	Analysis based on simulation
Mohar et al. [85]	RSS	RB	Low	Improved	No	No	Subceed	Subseed	Still	Continual	Analysis based on simulation
Zalzal et al. [86]	DV-Hop	RF	Low	Constant	No	No	Subceed	Subceed	Still	Continual	Analysis based on simulation
Nemer et al. [33]	Connectivity based	RF	Low	Compared	No	No	Regular	Regular	Still	Continual	Analysis based on simulation
Sun et al. [87]	PP-MAN	RB	Low	Improved	Yes	No	Subceed	Subceed	Moving	Continual	Analysis based on simulation
Kouroshnz et al. [88]	OPTEC	RF	Low	Improved	Yes	Yes	Subceed	Subceed	Moving	Recurrent	Analysis based on simulation
Alavijeh et al. [89]	EKF	RB	Low	Improved	No	Yes	Regular	Regular	Still	Continual	Analysis based on experiments
Chen et al. [90]	NLA-MB	RB	Low	Improved	Yes	Yes	Exceed	Exceed	Moving	Recurrent	Analysis based on experiments
Zhang et al. [91]	HMDS	RB	Low	Improved	No	No	Subceed	Subceed	Still	Recurrent	Analysis based on experiments
Shahzad et al. [92]	DX-Max DV-Hop	RF	–	Constant	No	No	Subceed	Subceed	Still	Recurrent	Analysis based on experiments
Tomic et al. [93]	RSS	RB	3-Dim	Constant	No	No	Regular	Regular	Still	Continual	Analysis based on experiments
Lv et al. [94]	Range based graphical	RB	Low	Constant	No	Yes	Regular	Subceed	Still	Continual	Analysis based on experiments
Li et al. [95]	LSDP	RB	Low	Improved	No	Yes	Regular	Regular	Still	Recurrent	Analysis based on experiments
Ou et al. [96]	DOUBLE-SCANHILBERT CIRCLES S-curves	RB	Low	Improved	No	No	Regular	Regular	Moving	Recurrent	Analysis based on simulation
Zhao et al. [97]	CDL	RF	Low	Improved	No	Yes	Regular	Subceed	Still	Recurrent	Experiment Based
Chang et al. [98]	DRL	RB	Low	Improved	Yes	Yes	Regular	Regular	Moving	Recurrent	Simulation-Based

LA localization algorithm, *RC* ranging criteria, *Dim* dimension, *CT* computation time, *CC* communication cost, *AS* anchor state, *ANO* anchor node outline, *EC* energy consumption, *ES* environmental setup, *RF* range free, *RB* range based, *SB* simulation based

$$RMS_{loc} = \sqrt{\frac{1}{N}\sum_{k=1}^{N} m_{act}^2[k] - m_{est}^2[k]} \tag{7}$$

Authors in [90] applied the NLA_MB algorithm to implement the localization process. To reduce mistakes, anchor node constraints such as movement path constraint and movement distance constraint are used to construct an optimization model. The greatest likelihood estimation approach seemed fine to get the coordinates with the help of anchor nodes. The heuristic approach is used for node distribution anchor nodes. The beacon node energy is limited, so the maximum mobility distance is limited. Then there is a movement distance constraint:

$$\sum\nolimits_{g=1,2\ldots\ldots.N_p-1} d(p_g, p_{g+1}) \le d_{th}, p_g \in P \tag{8}$$

This distance is between movement from $p_g top_{g+1}$ The ALE of sensor nodes is:

$$error(P) = \frac{\sum_{m\in V_R}^{N} \sqrt{\left|\left(x_m^R - x_m\right)^2 + \left(y_m^R - y_m\right)^2\right.}}{N} \tag{9}$$

For target tracking, Zheng et al. [91] presented a localization scheme that is also energy efficient with the flaw of high cost. It achieves incredibly accurate target tracking by utilizing portable hardware. The mobile sensor nodes can quickly amalgamate to the concerned channel through position information, save energy by avoiding superfluous transmission. The distance is given by between point $\left|d_1\right| and \left|d_2\right|$:

$$d_{st} = \sqrt{d_1^2 + d_2^2 - 2\left|d_1\right|\left|d_2\right|.\cos < sot} \tag{10}$$

The DV-maxHop approach described by Shahzad et al. [92]. This algorithm is far improved than DV hop. It is fast, simple, and can be practically implemented readily. The approach is tested by simulating numerous anisotropic variables on various topologies. Existing impediments, distributed and sensor nodes' deployment without any strategy, and radio transmission patterns are considered as parameters to evaluate the performance. The simulation results show that the technique beats existing range-free localization techniques for a wide range of parameters and that it may be used on anisotropic networks. Location estimation The error is defined as the difference between the actual and estimated node positions:

$$err = \sqrt{\left(x_{actual} - x_{est}\right)^2 + \left(y_{actual} - y_{est}\right)^2} \tag{11}$$

x_{actual} and y_{actual} is the actual and x_{est} and y_{est} is the estimated distance.

The algorithm proposed in [93] suggests a localization scheme in three-dimensional scenario. RSSI and AoA has been used as localization techniques. These algorithms are treated from two perspectives: cooperative and non-cooperative WSN. The scheme works on a non-convex objective function forms by localization measurement techniques "RSSI" and "AoA". The SDP relaxation technique and the generated non-convex objective function together built a convex framework. RMSE for node coordinates x_i and $\overbrace{\quad x_i \quad}$.

$$RMSE = \sqrt{\sum_{i=1}^{M_c} \frac{\left|\left|x_i - \overbrace{\quad x_i \quad}\right|\right|^2}{M_c}} \tag{12}$$

For efficient cooperative positioning in WSNs, Lv et al. [94] developed a space–time hierarchical graph. A bootstrap percolation technique based on soft constraints was employed to manage the activities of sensor nodes. Authors in [95] describe an innovative algorithm for obtaining a global map for the intended objective. The simulation results suggest that the proposed technique improves scalability and accuracy, and it is also effective at measuring noise. The noise in distance measurement is estimated as:

$$\hat{d}_{ij} = d_{ij}(1 + \gamma.N(0,1)) \tag{13}$$

The RMSE can be derived from

$$rmse = \sqrt{\frac{\sum_{i=1}^{n}\left(X_{rel}^{i} - X_{est}^{i}\right)^2}{n}} \tag{14}$$

$\hat{d}_{ij}$ is the distance with noise factor and d_{ij} is actual distance between nodes.

Authors in [96] suggested a tactic based on path observation for the dynamic anchor node. The obstructions in the sensing field impede the localization process. This scenario can be handled using the proposed obstacle-resistance trajectory. According to simulation data, this increases the number of correctly localized nodes while decreasing the localization error. The localization error can be expressed as follows:

$$e = \frac{\sum_{i=1}^{n-1}\sqrt{(x_i - \hat{x}_i)^2 + (y_i + \hat{y}_i)^2}}{[(N - M) \times r]} \tag{15}$$

Zhao et al. [97] suggested a localization technique based on hop distance. This hop count information gets exchanged from anchor to sensor nodes and vice versa. In the literature, these algorithms are referred to as connectivity-based algorithms. For localization, the authors presented a combined and differentiated localization (CDL) technique. The proposed approach is implemented with range-based techniques as measured by RSSI. The proposed method enhances accuracy and produces consistent results.

A Differential Relative Location (DRL) technique was proposed by Chang et al. [98]. The schemes work through the identification of neighboring nodes of anchor nodes. The relative location is estimated by suggested path planning approaches by reducing energy consumption. The authors demonstrate the algorithm's performance through experimental findings. The total energy consumption is the sum of the energy consumed while turning, moving, tone signal and beacon nodes as follows:

$$E(P,\rho) = E_{move} + E_{turn} + E_{beacon} + E_{tone} \tag{16}$$

The comparison in Table 2 shows that localization algorithms are not able to deal with the mentioned challenges to overcome the problem all alone. So, it is a need of the day to implement them with some advanced algorithms like machine learning or nature-inspired evolutionary algorithms. The next sub section is related to the above stated issues.

4.2 Analysis for Localization Techniques with ML Algorithms

This analytical survey is based on various machine-learning techniques for node localization in WSN. Various ML and localization algorithms applied in various kinds of literature have been discussed along with the evaluation parameters broadly based on localization error.

The author [99] proposed a feature extraction method based on the reading and position of each sensor in a zone where a radiation source is detected. Asif et al. [100] create and present a distance vector hop-based technique for safe and robust localization in the presence of hostile sensor nodes, which produce inaccurate position estimates and imperil WSN operation. Abdullah et al. [101] provide a DFL framework for feature recognition and extraction that includes deep autoencoders based on the "restricted Boltzmann machine (RBM)" with many CNN layers with. Kagi et al. [102] created a hybrid model calledt the "Lion Assisted Firefly Algorithm" (LAFA). A parametric analysis of the proposed algorithm is performed at this conference by altering the evaluation parameter in "LAFA". Gang et al. [103] offer a prediction in "MI-UWSNs" based on ML to improve the accuracy of randomly deployed sensor "Rx nodes" via anchor "Tx nodes".

To overcome the challenge of localization, Robinson et al. [41] propose a 3-dimensional "Manifold" and "Machine Learning" based approach for localization. Machine Learning is utilized in WSNs to discover problematic network nodes and compute the finest solution to deal with the challenges with real-time localization. Using a "Single Hidden Layer Extreme Learning Machine" and a "Two Hidden Layer Extreme Learning Machine", Liouane et al. [104] proposed ways for node localization in WSN. The solutions offered are employed in a variety of "Multi-hop" WSN deployment scenarios. To improve the accuracy in localization schemes, a "neural network" based classification is constructed. The performance is compared with other techniques. The authors also developed a data storage structure in a distributed manner and a platform with Redis that considers storage load. Hu et al. [105] employ cloud computing to create a revolutionary multi-interior indoor localization system. According to a previous study, there is always concern about avoiding a blockage and interference in signal. Wang et al. [40] proposed the "Kernel Extreme Learning Machines" based on the "Hop-count Quantization" node localization approach. Rashdan et al. [106] investigated and analyzed thirteen ML strategies. These methods are applied to mobile terminals with fingerprinting localization.

Several DM-MIMO topologies are used to examine the characteristics influencing mobile terminal localization. The results reveal that KNN outperforms all thirteen algorithms studied.

You et al. [107] explored a method for reducing the complexity of the "multiple source localization" problem by using an RSS value. Maghdid et al. [108] developed a technique for smart city indoor localization. The proposed "RNN-based long Short-Term Memory" strategy is a type of "RNN" technique. Bhatti et al. [109] used a combination of "supervised", "unsupervised", and "ensemble" ML approaches to create an outlier identification system. This "if Ensemble" is developed for indoor localization schemes.

Kim et al. [110] proposed a method for pre-processing a signal in preparation for NN fingerprinting. The proposed approach provides a solution for the actual inside environment, such as a building with corridors and rooms that generate hindrances in signal transmission. It recovers the signal's Multiview CSI using NMF and completes the sparse matrix. The corridors that cause problems in Multiview CSI are resolved using CSI modifications related with a variance in inference-based machine learning. The proposed method yields an 89 cm improvement in localization accuracy. LF-DLSTM was proposed by Chen et al. [111]. This approach was developed for indoor environments using fingerprinting method through wifi. The proposed strategy is compared with traditional indoor localization techniques. The data show that its performance has improved. The tests are examined both indoors and outdoors. When the proposed method is compared to standard indoor localization techniques. The consequences of its improved performance are visible. To discover the defective linkages, Srinivasan et al. [113] offered an unassertive approach and developed the ML-LFIL technique. ML-LFIL is a three-stage technique that investigates the typical transmission flow, average flow transmission rate, latency, and packet loss to identify and localise broken links. By comparing the routing traffic scenarios, the investigation is examined. SVM, MLP, and RF are the ML techniques employed in the 3-stage model. Distance measurement was viewed as a closed-loop problem by Yan et al. [114]. The authors created an algorithm based on consensus and UKF to estimate the sensor node's location. By combining direct and indirect measurement, the impact of harmful data can be reduced.

Panayiotou et al. [115] suggested a solution to the problem of imprecise and failing localization. The model is trained using the network's current and historical occurrences. To retrieve the prior data, a Gaussian process classifier is developed to predict and model the occurrence of failures. Berz et al. [116] suggested an Indoor Positioning System with many sensors based on EVR and ANN. The method can estimate the position in a 3-D network. Prasad et al. [117] suggested an RSSI-based SVMMIMO system based on Gaussian Process Regression. The suggested method secures the position by training a machine-learning model on noise-free RSSI data. The traditional GP method and its variant, numerical approximation GP, are used. NaGP is proven to be more suitable for predicting two error bars to localize the objects.

Almeida et al. [118] proposed a less expensive and more successful method for localizing a non-static robot. The method employs machine learning and signal processing techniques. The robots are located using a sonar, which can detect objects in all directions. The performance of several classifiers such as "kNN", "SVM", "OPF", "MLP", and "Bayes classifiers" has been investigated. The results reveal that OPF beats all others. Amri et al. [119] suggested a geographic routing mechanism based on a weighted centroid localization technique, in which the coordinates of unknown nodes are determined using a fuzzy logic method.

Tariq et al. [121] provided a method for exploring how machine learning algorithms used for categorization might increase localization accuracy and noise by selecting a specific node deployment strategy. The trials are carried out in a 3mx3m indoor space. The classification approaches RF, SVM, k-NN, and Bayes Net were tested. A deep learning method for "Device-Free Localization" and "Activity Recognition" is proposed in [122]. A "generalized regression neural network" is used in the first portion. In the second layer, instead of RBF, a specific linear layer was used as the activation function to generate four reference nodes. Wymeersch et al. [127] proposed a method for reducing range error residing in the physical layer. The ranging error is calculated using two non-parametric regressors. The proposed work is authenticated using FCC-compliant UWB radios. Experiment findings show that the proposed approach works effectively in a variety of practical circumstances.

Table 3 Analysis for Localization and ML Techniques in WSN

Year of publication	References	Authors	Objective	Applied technique	Comparisons	Scenario	Vigorous	Application	Accuracy	Localization error	Area	Outcome
2023	[99]	Abdelhakim et al	A method for extracting features from the readings and positions of all nodes in the radiation detected zone	Decision tree	Random forest implemented by other authors	Outdoor	No	Distributed sensor network	Medium	Reduced	Distributed sensor network	Improved accuracy and execution time
	[100]	Asif et al	Estimates the sensor node location by neutralizing the attacks	–	Basic DV-Hop	Outdoor	Yes	Security	Medium	Reduced	Hostile environment	Secured localizations algorithm
	[101]	Abdullah et al	Node localization dimensionality reduction using deep learning techniques	CNN	–	Outdoor	No	Device-free localization	High	–	General simulation based	Reduced dimensions Low SNRs 98% accuracy
2022	[102]	Kagi et al	DNN-based method trained with measured distance-based features: RSSI and AoA	DNN	Compared on noise variance	Outdoor	Yes	Evaluated on LAFA	Medium	Reduced	3 D Scenarios	LAFA hybrid model is introduced
	[103]	Gang et al	To achieve the sustainable development goals (SDGs)	Linear regression	Accuracy on varying number of sensor Rx nodes	Indoor	Yes	IIoT-based MI-UWSNs	High	–	SDG 9 SDG 14	Improved accuracy for IIoT-based MI-UWSNs
	[41]	Robinson et al	Algorithm for node localisation based on 3-dimensional manifold learning	Manifold Learning	PDR, TOA, RSSI	Outdoor	Yes	Real Time Problems	Medium	Reduced	3-D Manifold	Reduced energy consumption

Table 3 (continued)

Year of publication	References	Authors	Objective	Applied technique	Comparisons	Scenario	Vigorous	Application	Accuracy	Localization error	Area	Outcome
2021	[104]	Liouane et al	Propose SHL-ELM/THLELM based methods for localization	THL-ELM	Single hidden layer ELM	Outdoor	No	Range-free localization	Medium	Reduced	–	Reduced localization error
	[105]	He etal	Apply kernel regression to anisotropic WSN node localization	Regression	Classical DV-Hop	Outdoor	Yes	Anisotropic WSN	High	–	–	Enhanced accuracy and stability
	[105]	Hu et al	Indoor localization using cloud computing	Neural Network	KWNN ANN-SVM	Indoor	Yes	Real time scenario	Medium	–	Multi indoor environment	Higher accuracy less power consumption, High system magnitude

Table 3 (continued)

Year of publication	References	Authors	Objective	Applied technique	Comparisons	Scenario	Vigorous	Application	Accuracy	Localization error	Area	Outcome
2020	[40]	Wang et al	Kernel ELM based on Hop-count quantization	ELM	Fast-SVM GADV-Hop	Outdoor	Yes	–	Medium	Reduced	100 m^2 area	Low Localization error
	[106]	Tahat et al	Localization in a DM-MIMO system based on RSS fingerprinting and machine learning	13 ML Techniques	–	Indoor	No	Mobile scenarios	–	–	Institute campus	K-NN outperforms among all
	[107]	You et al	RSS-based MSL (multi source location) problem	BL	MS learning	Outdoor	No	MS learning	–	–	25 m^2	The issue of parametric learning problem of dictionary has been resolved
	[108]	Maghdid et al	A unique indoor navigation method based on LSTM	k-NN	–	Indoor	No	City infrastructure	Medium	–	KIOS dataset	plays admirably in a realistic indoor setting
	[109]	Bhatti et al	Technique for detecting outliers in a Wi-Fi indoor localization setting	SVM, KNN Naïve Bayes RF	Results based on mentioned ML techniques	Indoor	No	Wi-Fi indoor areas	High	–	UCI data set	Outlier Detection 97.8% No Outlier Detection 2% Improved accuracy
	[110]	Kim et al	Designing a signal pre-processing method for NN fingerprinting	NN	CiFi, Biloc, SVR., DNN with NMF	Indoor	No	Empirical building environment	Medium	–	Building structure of 3 corridors	Accuracy improved by 0.89 m,

Table 3 (continued)

Year of publication	References	Authors	Objective	Applied technique	Comparisons	Scenario	Vigorous	Application	Accuracy	Localization error	Area	Outcome
2019	[111]	Chen et al	A deep LSTM method based on local features	DL	ELM DELM	Indoor	No	Fingerprinting DB	Medium	Reduced	Research Lab, Office building	18.98% noise reduction with error reduction by 53.46%
	[112]	Fan et al	Expectation maximization used with Gaussian mixture models to classify LOS and NLOS	Unsupervised	LS-SVM	Outdoor	Yes	Objects falling in NLOS	Medium	–	–	86.50% correct rate 12.70% FN 0.8% FP rate
	[113]	Srinivasan et al	Three-stage machine learning-based technique: ML-LFIL	SVM, PCA RF, MLP	Comparison of four mentioned algorithms	Outdoor	Yes	Fault detection	High	Reduced	Mininet platform	97% of accuracy RF out performed and SVM is worst

Table 3 (continued)

Year of publication	References	Authors	Objective	Applied technique	Comparisons	Scenario	Vigorous	Application	Accuracy	Localization error	Area	Outcome
2018	[114]	Yan et al	To develop consensus-based unscented Kalman filtering (UKF) algorithm	–	Stochastic weights	Outdoor	Yes	Underwater WSN	Medium	Reduced	Moving underwater target of 400 × 100 × 200m3	Maximized contributions for stable measurements minimized contributions of less stable one
	[115]	Panayiotou et al	Fault localization approach	Statistical ML	GBCM experiential	Outdoor	No	transparent optical networks	Medium	–	Optical network	Network costs associated with the fault localization operation has been reduced
	[116]	Berz et al	Multi-sensor IPS	K-mean SVR ANN	–	Indoor	No	3D Localization	Medium	Reduced	a laboratory (10 m × 7 m)	Error is 80.7 cm for ANN 73.7 cm for SVR
	[117]	Prasad et al	Uplinking RSS data with ML techniques in a distributed MIMO system	CGP NaGP	CGP with NaGP method	Outdoor	Yes	Position estimation	Medium	–	100 m × 100 m Service area	Improved RMSE performance
	[118]	Almeida et al	A location scheme for robots standalone furniture ML and omnidirectional sonar	Bayes classifier, MLP, k-NN SVM, OPF	Comparison among mentioned ML Techniques	Indoor	No	Mobile robot localization	High	–	A plant	Accuracy 98.13% Test time of 17.4 µs Sensitivity 89.73% Specificity 98.97%

Table 3 (continued)

Year of publication	References	Authors	Objective	Applied technique	Comparisons	Scenario	Vigorous	Application	Accuracy	Localization error	Area	Outcome
2017	[119]	Amri et al	A range-free localization algorithm for WSN using RSSI information	Fuzzy logic	–	Outdoor	No	Geographic routing	Medium	Reduced	100 m × 100 m field size	Energy efficient with improved network lifetime
	[120]	Khatab et al	An auto encoder based Deep ELM indoor localization method	Deep ELM	Conventional DL based on ELM	Indoor	Yes	–	Medium	–	Institute's laboratory	Applied large training data to performance enhancement
	[121]	Tariq et al	Accurate tag less indoor person localization	Bayes Net k-NN, SVM RM	Comparison among given ML techniques	Indoor	No	Human localization	Medium	Reduced	3 m × 3 m room	Random forest is performing best
2016	[122]	Wang et al	A deep learning approach for DFLAR	DL	Features of conventional handcrafts	Indoor	No	–	High	–	laboratory and an apartment	High accuracy
	[123]	Zheng et al	Localization and Tracking algorithm based on energy efficiency	Adaptive weighted KNN	k-NN WKNN	Indoor & outdoor	Yes	–	Medium	–	Indoor 200 m^2, outdoor LOS area	Energy efficient Improved target positioning
2015	[124]	Jiang et al	Fibre Bragg grating (FBG) sensors-based localization in a low velocity area	ELM	Experimented 36 times	Outdoor	No	Reinforced fiber	Medium	–	240 mm^2 area	High accuracy in an area with low velocity
2013	[125]	Park et al	To develop a localization algorithm using ensemble learning and SVR	ESVR	–	Indoor	No	–	Medium	–	–	Good predictor

Table 3 (continued)

Year of publication	References	Authors	Objective	Applied technique	Comparisons	Scenario	Vigorous	Application	Accuracy	Localization error	Area	Outcome
2012	[126]	Park et al	To develop a supple location approximation algorithm using GRNN	ANN	Existing range based techniques	Indoor	No	–	Medium	–	20×20 m2	Improved performance with no additional hardware
	[127]	Wymeersch et al	SVM and GP as Nonparametric ML techniques to find the error	SVM GP	–	Indoor	No	LOS & NLOS	–	Reduced	–	Improve localization performance

Table 3 focuses on an analytical discussion of various machine learning-based localization algorithms over environmental scenarios, application areas, accuracy, error, and their outcome. From the above analysis, it has been observed the accuracy achieved from these algorithms is average. To gain high accuracy we need to implement them with some advanced techniques.

4.3 Analysis for Localization Techniques Based on Optimization and ML Techniques

An analytical discussion is shown in Table 4 which is based on various machine-learning techniques for node localization in WSN with optimization techniques. Various ML, optimization and localization algorithms applied in several works of literature have been discussed along with the evaluation parameters broadly based on localization error and optimization function.

Chadha et al. [128] use data from 192,555 satellites to train "deep learning" models such as tailored "CNN" in this study. To reduce the effect of noise in signals the dataset was pre-processed and then it was displayed to analyze data pixel intensities using exploratory data analysis. The RMSE was determined using real and expected measurements.

$$RMSE = \sqrt{\frac{(Actual - Predicted)^2}{Total\,number\,of\,observation}} \tag{17}$$

The authors [129] offer a machine-learning technique for handling the RobotAtFactory 4.0 localization challenge. The goal is to collect an onboard camera's relative posture concerning fiducial markers, i.e., "ArUcos" and apply machine learning to determine the robot's attitude. Among few tested algorithms Random Forest Regressor delivered the best results, with a millimeter-scale error. Author in [34] designed an "Optimised Localization Learning Algorithm". The performance is evaluated using indoor and outdoor settings on different anchor nodes.

$$\min_{\eta, \xi, b} \sum_{i=1}^{a} \|\eta \Delta \bar{x}_i - \Delta x_i\|^2 + \|\xi \Delta \bar{x}_i - \Delta x_i\|^2 \tag{18}$$

where x_i are relative coordinates and $\bar{x}_i$ are absolute coordinate.

The authors suggested an optimized localization algorithm implemented with Q learning technique in [37].The proposed work locates nodes by constructing all possible paths via k-fold algorithm and selecting the best path to transmit the packets. The proposed technique's effectiveness was thoroughly investigated. The following approach can be used to calculate the RLE as a percentage:

$$RLE\% = \left(\frac{1}{N} \sum_{a=1}^{N} RLE_a \right) \times 100 \tag{19}$$

The authors of [130] proposed an innovative scenario to evaluate the performance under an indoor localization environment and to estimate the occupancy-count using 5G "Ultra-Dense Networks". In [131], an upgraded DV-Hop localization technique is constructed based on a suggested selective opposition class topping optimization (SOCTO). The SOCTO method was used to improve the placements of nodes. The following equation represents the objective function of the proposed DV Hop based is SOCTO scheme:

Table 4 Analysis for ML and Optimization Techniques for Localization

Author & Refernece	Techniques used for localization	Technique of machine learning	Hybrid ML	Applied optimization technique	Technique for optimization	Specification
Chadha et al. [128]	RF	CNN	No	No	–	Improved precision
Klein et al. [129]	RSS	Random forest regressor	No	No	–	Low error
Yadav et al. [37]	RSS	Q-Learning	No	Yes	–	Reduced error with optimal node coordinates
Habashan et al. [130]	RSS fingerprinting	kNN	No	No	–	Reduced indoor localization
Mohanata et al. [131]	DV-Hop	–	No	Yes	Selective opposition class topper algorithm	Reduced ALE
Yadav et al. [132]	RSS	Supervised learning	No	Yes	K-Fold	Energy efficient with reduced distance error
Chen et al. [133]	RSS	Genetic algorithm	No	No	–	Approximate the node with reduced error
Shen et al. [134]	RSS	DNN	No	No	–	Energy effieicnt
Guo et al. [135]	TDoA	LR	No	No	–	Low error, high accuracy
Kotival et al. [136]	RSS	SVR	No	Yes	Cuckoo search technique	Reduced time complexity and error
Quanqian Ren et al. [137]	RSS	GA	No	No	–	Reduced localization error
Cai et al. [138]	DV Hop	GA	No	No	–	Reduced error
Annepu et al. [83]	Multilateration RSS	ELM	No	Yes	OSEL	Improved accuracy and computational complexity
AnushaKS et al. [140]	Device free localization	SVR	No	NO	–	Reduced error
Rauchenstein et al. [141]	TDoA	Classification & regression	Yes	No	–	Calibrated localization error, improved accuracy
Wen et al. [142]	MaxHop	–	No	Yes	PSO	Low Localization error
Zhang et al. [143]	RSS	ANN	No	No	–	Minimized error Maximized accuracy

Table 4 (continued)

Author & Refernece	Techniques used for localization	Technique of machine learning	Hybrid ML	Applied optimization technique	Technique for optimization	Specification
Fang et al. [144]	RSS fingerprinting	WKNN	No	No	OWKNN	Optimal node localization High Accuracy Node placement, and anchor nodes doesn't matter
Pheomphon et al. [69]	RF	Fuzzy logic, ELM	Yes	Yes	PSO	Minimised time complexity, error and high accuracy
Rahmoun et al. [75]	RSS	–	No	Yes	BA	Depreciated error with low computing time
Sankalp et al. [145]	Trilateration	–	No	Yes	BOA	Reduced error and computing time, improved accuracy and consistency
Zhang et al. [146]	DV-Hop	SVM	No	Yes	2-Hop MS	Improved accuracy
Sharma et al. [147]	DV Hop	–	No	Yes	TLBO	Improved precision, greater positioning coverage, and lower energy usage
Banihashemian et al. [148]	RF	ANN	No	Yes	PSO	Depreciated error, energy efficient, less storage requirement
Kang et al. [149]	Graph based localization	CNN + SVM	Yes	No	–	Very high accuracy Very low localization error Real time Scenario
Sun et al. [150]	RSS	Bayesian	No	No	–	Reduced ALE
Wang et al. [151]	RSS	Bayesian	No	No	–	Energy-efficient
Li et al. [152]	RSS	PCA	No	No	–	Outlier detection

Table 4 (continued)

Author & Refernece	Techniques used for localization	Technique of machine learning	Hybrid ML	Applied optimization technique	Technique for optimization	Specification
Barcelo et al. [153]	RSS	LR &NN	Yes	No	–	Improved accuracy Reduced error Localizes maximum targets Real time applications
Balaswamy et al. [154]	AKF	–	No	Yes	PSO	More accurate
Assaf et al. [155]	RF	ANN	No	No	–	Exceeded Accuracy
Wei et al. [156]	Hop-count based	SVM Fuzzy Logic	Yes	No	–	High Precision Addresses border problem and coverage hole problem time complexity reduction
Nordin et al.[157]	RSS	ANN	No	Yes	PSO	Improved accuracy and distance estimation No additional component needed
Permpol et al. [158]	RSS	ELM	Yes	Yes	MSO	Practical, robustness, Reduced ALE, More accurate
M.Bernas et al. [159]	RSS	K-means, fuzzy-c-means ANN	Yes	No	–	Amended accuracy Learning process speedup
Ashish et al. [159]	RSS	FFANN	Yes	No	–	Rapid conjunction, Subceeded computation cost Low network cost Fast speed of convergence

$$f(a,b) = \min(\sum_{i=1,2,\ldots,M} \left| \sqrt{(a-a_i)^2 + (b-b_i{}^2)} - p_{ik}^{Mod} \right|) \tag{20}$$

A hybrid scheme that combining "K-fold" and "supervised learning" is proposed to improve the energy efficiency and reduce the error in [132]. Here the Localization process has been performed by calculation round trip time. RTT is round trip time that would be calculated when the source sends the acknowledgment at time t_1, and destination gives the feedback at time t_2:

$$RTT = t_2 - t_1 \tag{21}$$

The error can be calculated by differentiation the both types of error the actual and the estimated one.

$$e = \sqrt{(x_i - \hat{x}_i)^2 + (y - \hat{y}_i)^2} \tag{22}$$

This paper presents an energy-efficient localization technique based on clustering named as [133]. The proposed "ECGAL" approach consumes less energy and extends the life of wireless networks. The results of the experiments show that the proposed technique approximates the node position with low localization error. The difference between the estimated and real location point should always be taken into account to calculate the localization error, as shown in the equation below:

$$LE_x = \frac{1}{R}\sqrt{(p_{ux}^0 - p_{ux})^2 + (q_{ux}^0 - q_{ux})^2} \tag{23}$$

Shen et al. [134] developed a localization method based on RSSI value calculation. "DNN" is used for basic maintaining the relationship between the RSSI value of nodes and their placement in the network to improve the performance. The strategy necessitates the dataset for training (X), given in the equation below in the range 1 to T.

$$X = \{(a_i, \overline{x}_{s_j}^t \left| \forall a_i \in A, s_j = p\left(a_i, t\right), 1 \le t \le T)\right\} \tag{24}$$

Guo et al. [135] suggested a movable target localization approach for underwater sensor networks. For range estimation, this strategy employs the TDoA method. The interactive multiple model approach reduces the effects of mobile sensor node effects such as placement mistakes. Node time synchronzsation and localization are combined during iteration to increase accuracy. The overall "state estimation" ($\hat{x}_k$) and the total "error covariance matrix" C_k of each model can be written as:

$$\hat{x}_k = \sum_{j=1}^{z} \hat{x}_k^j v_k^j \tag{25}$$

$$C_k = \sum_{j=1}^{z} v_k^j (C_k^j + (\hat{x}_k^j - \hat{x}_k)(\hat{x}_k^j - \hat{x}_k)^T) \tag{26}$$

Singh et al. [136] optimized the machine learning Support Vector Regression model to achieve a low Average Localization Error for evaluating ideal network parameters. The authors presented three approaches based on feature standardization to improve the prediction accuracy of ALE: S-SVR, Z-SVR, and R-SVR. The Optimization Function is given by:

$$F(x_i, y_i) = \frac{1}{M} \times \sum_{j=1}^{M} (D_{ij} - D'_{ij})^2 \tag{27}$$

here x_i, y_i are the coordinates of the sensor nodes. D_{ij} is the actual distance between nodes and $D_{ij}\prime$ is the estimated distance. M is the number of anchor nodes.

Qianqian et al. [137] offer an approach by merging the "RSSI" quantization and evolutionary algorithm of localization. The proposed method is divided into three stages: Dividing the sensing region into numerous rings, determining ring overlap, and researching density-based grouping techniques. Genetic algorithms based on an elitist preservation strategy decide the breadth of the rings. The distance loss model can be expressed through the below equation:

$$RSSI(d) = RSSI(d_0) - 10n\log_{10}\frac{d}{d_0} \tag{28}$$

Cai et al. [138] present a model bordered by "hops and weights" based on mathematical analysis. The suggested approach employs a "genetic algorithm" to solve the "MW-GADV-hop" problem. The average localization error (ALE) is calculated as follows:

$$\text{ALE} = \frac{100}{(N-n).R} \sum_{i=1}^{N-n} \sqrt{(x_i^* - x_i)^2 + (y_i^* - y_i)^2} \tag{29}$$

Authors in [83] developed a UAV that employed "ANN" method for any "Unmanned Ariel Vehicles" in WSN. In the learning phase, the technique takes only one iteration. Simulation is used to demonstrate the results. The I/O vectors of the given "ELM" approach are theoretically connected as:

$$\sum_{h=1}^{H_E} \beta_h g\left(w_h^T \hat{r}_m + b_h\right) = [\hat{x}_m, \hat{y}_m]^T, m = 1, 2, \ldots, M \tag{30}$$

$$\sum_{h=1}^{H_E} \beta_h g\left(w_h^T \hat{r}_i^t + b_h\right) = [\tilde{x}_i^t, \tilde{y}_i^t]^T, m = 1, 2, \ldots, M \tag{31}$$

Anusha et al. [139] suggested a "link distance-WVM" model that perform localisation a 3D indoor environment. The selection of SVM was motivated by its adaptability. In the expression below, the target's position is given as the link distance ratio R:

$$Link\,Distance\,Ratio(R) = \frac{\text{Target distance from transmitter}}{\text{Link Distance}} \tag{32}$$

Rauchenstein et al. [140] proposed a TDoA-based localization technique. A classification and regression technique of machine learning is combined with TDoA to correct the localization inaccuracy target tracking. The below confusion matrix can capture both measurements:

$$Confusion\,Matrix = \begin{bmatrix} 0\,classified\,as\,0 & 0\,classified\,as\,1 \\ 1\,classified\,as\,0 & 1\,classified\,as\,1 \end{bmatrix} \tag{33}$$

Wen et al. [141] used an isotropous WSN to implement a localization technique. To construct LAEP, they inherited predicted hop advancement. As demonstrated by, the distance error between the anchor nodes is commonly utilized as a fitness function:

$$\text{fitness(x, y)} = \sum_{i=1}^{N_a} \eta f_i^2 \tag{34}$$

$$f_i = \left| \sqrt{(x - x_i)^2 + (y - y_i)^2} - \hat{d}_{i-j} \right| \tag{35}$$

x, y are the node coordinates, i is the ith node in the network. $\hat{d}_{i-j}$ is the estimated distance. The distance error can be represented by the "mean distance error" (MDE) and "distance estimation error" (DER):

$$\text{MDE} = \frac{\sum_{i=1}^{N_a} \sum_{j=1}^{N_L} \left| d_{i-j} - \hat{d}_{i-j} \right|}{N_a . N_L} \tag{36}$$

$$\text{DER} = \frac{\left| d_{i-j} - \hat{d}_{i-j} \right|}{d_{i-j}} \tag{37}$$

$$\text{localizable percentage} = \frac{N_L}{N_u} \times 100\% \tag{38}$$

The localization percentage can be calculated by ration of N_L and $N_{u,}$ i.e. ratio of localized and unknown nodes.

Sun et al. [142] suggested a device-free localization strategy based on "ANN". According to the experimental results, the suggested approach achieves average accuracy for device-free localization. The trained ANN model may estimate the target by using the x and y coordinate values and their RSS value:

$$(\hat{x}, \hat{y}) = F(\Delta rss'_{1,} c_1, r_1, \Delta rss'_2, c_2, r_2, \ldots, \Delta rss'_K, c_K, r_K) \tag{39}$$

Fang et al. [143] proposed OWKNN, which performs well in noisy environments. This algorithm is a hybrid of the AKF and MA algorithms. The first method reduces noise in RSSI signals and another one to sensor nodes. The OWKNN delivers the highest level of positioning precision. The WKNN estimated node location is as follows:

$$(x, y) = \sum_{l}^{K} w_l(x_l, y_l) \tag{40}$$

The optimization model is:

$$\text{minimise : y = g(x)} \tag{41}$$

This model is based on estimation of fingerprinting data and their optimal weights.

The original centroid approach was improved by Phoemphon et al. [144]. ELM and fuzzy logic Machine learning techniques are used to combine the methodology. Fuzzy logic focuses on low node density and small area coverage, whereas ELM is used in the vigorous localization phenomenon. To minimise unequal node dispersal, the resulting force vectors are cooperated over PSO. The mean of the reference nodes' two-dimensional locations:

$$\left(x_{est}, y_{est}\right) = \left(\frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}, \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i}\right) \tag{42}$$

x_{est}, y_{est} are the estimated coordinates after localization.

Mihoubi et al. [69] developed an approach by combining "bat algorithm" with the node localization algorithm The goal function is calculated based on the mean square error between actual and estimated distances of the coordinates. It is computed as follows:

$$f(x,y) = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(x-x_i)^2 + (y-y_i)^2} - \hat{d}_i \tag{43}$$

Equation (44) shows the average execution time for the proposed algorithm

$$\text{Average excution time} = \frac{\sum_{\text{i=1}}^{\text{n}} \text{execution time}}{\text{n(number of sensor node)}} \tag{44}$$

Arora et al. [75] suggested a butterfly optimization-based localization approach. The approach was tested on 25 to 150 sensor nodes by the author. When compared to PSO and firefly algorithms, the former has proven to be more consistent and accurate. The fittest butterfly/solution g is represented as:

$$x_i^{t+1} = x_i^t + \text{Levy}(\lambda) \times (g^* - x_i^t) \times f_i \tag{45}$$

x_t^{t+1} represents the local search:

$$x_t^{t+1} = x_i^t + \text{Levy}(\lambda) \times (x_j^t - x_k^t) \times f_i \tag{46}$$

The LSVM-PCS approach described by Wang et al. [145] or node localization. This strategy is developed by amalgamating SVM and PCS. Using an SVM approach, each sensor node may be classified or localized into a single grid. When a node is assigned to a specific grid, PCS is used to estimate its location. The "two-hop mass-spring" is applied in this work for enhancing the results fetched from the proposed idea. The decision function f(x) is:

$$f(x) = \sum_{i=1}^{K} a_i^* y_i K\left(X_i, X\right) + b^* \tag{47}$$

The optimized energy consumption is achieved, which is defined as:

$$E = \sum_{i=1}^{K} E(S_i) \tag{48}$$

Sharma et al. [146] presented an approach named "MDV-TLBO" for node localization. This approach incorporates DV-Hop and the "teaching learning-based optimization" technique. The optimization technique used enhances localization accuracy. The simulation results demonstrated better accuracy and location coverage, as well as reduced energy use. average hop distance or hop size denoted as:

$$HopSize_i = \frac{\sum_{i \neq j} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sum_{i \neq j} hop_{ij}} \tag{49}$$

The distance error is:

$$d_{ij}^{error} = \left| D_{ij}^{actual} - D_{ij}^{estimated} \right| \tag{50}$$

Banihasemian et al. [147] suggested a neural network-based localization approach with range-free localization algorithms needed several neuron techniques. PSO is used to locate neurons in the model's hidden layer. The goal function is developed with accuracy and data storage in mind. It decreases localization errors and storage needs. We can estimate the Pm i141 maxP errori given in Eq. (51). Equation (52) calculates the storage cost concerning the number of anchor nodes.

$$\sum_{i=1}^{m} \max P_{error_i} = m * \max P\_error \tag{51}$$

$$\text{cost\_weights} = min\left[\frac{(m * HN_1 + HN_1 * HN_2 + HN_2 * 2)}{m * 100 + 10200} * 4, 1 \right] \tag{52}$$

Kang et al. [148] proposed an approach using one-dimensional "CNN" and "SVM" ML approaches to detect leakage in water treatment plants. The graph depicts the infrastructure network of real water pipelines, with virtual spots representing leakage places. The leakage points can be found by comparing the graphs that have values above than mentioned. The approach decreases inaccuracy during the localization of the leaking spot. The ensemble 1D-CNN-SVM probability is defined as:

$$P(Y_c | C_{nn}, S_{vm}) = \alpha \times w_{cnn} \times P(y_c | C_{nn}) + (1 - \alpha) \times w_{svm} \times P(y'_c | S_{vm}) \tag{53}$$

Sun et al. [149] suggested an iterative approach for counting and localising numerous targets. The method relies on the concept of dynamically mitigating dictionary mismatches. The suggested method operates in two parts, first remembering the off-grid targets, counting them, and estimating the parameters by recovering joint sparce signals, and then solving the joint optimisation issue using a variant of the VBEM and VBM algorithms. According to the simulation findings, this algorithm performs well in counting and error reduction. The estimated count of target is given by K^.

$$\hat{K} = \|\hat{w}\|_0 \tag{54}$$

The ALE is defined as:

$$Avg.Error = \frac{\sum_{k=1}^{K} \|\tau_k - \hat{\theta}_k\|_2}{K} \tag{55}$$

Wang et al. [150] offered a solution that included two localization strategies to address the problem. In the suggested method, sensors simply provide the link to the base station rather than RSS data. The first localization method uses a Grid-based maximum likelihood technique to reduce processing costs. Another one uses a “particle filter” to perform target tracking and localize the nodes. Experiments for binary work mode are carried out, demonstrating the enhanced performance of the suggested task. The covariance for the estimated target is given by:

$$\mathrm{cov}(X_t) \approx \sum_{i=1}^{N_{PF}} w_t^i (X_t^i - \hat{X}_t)(X_t^i - \hat{X}_t)^T \tag{56}$$

Outliers make it difficult for localization algorithms to reach the required accuracy. To address it, authors in [151] presented a strategy using a powerful PCA machine learning technique. The authors created a non-convex objective function to solve it. Correa et al. [152] produced a pedestrian activity tracking approach in an indoor environment. Janapati et al. [153] proposed a method for the localization of sensor nodes in a cooperative network by employing the “PSO” and “AKF” algorithms. Because of its linear filtering property, the Kalman filter is used to estimate the position of sensor nodes. The divergence or adaptation for adaptive filtering is given in Eq. (57).

$$FIT = ROD = \frac{tr(\hat{C}_{vk})}{tr(C_{vk})} \tag{57}$$

Assaf et al. [154] suggested an efficient technique for sensor node localization. The approach is well-suited for complicated WSNs in which signals are broadcast. The ANN machine learning technology is used to generate distance estimation. The NRMSE is calculated through Eq. (58).

$$\mathrm{NRMSE} = \left(\sum_{i=1}^{N-N_a} \sqrt{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2})/((N - N_a)R \right) \tag{58}$$

FCMTSR was proposed by Zhu et al. [155] to minimise data obtained from diverse sources. To decrease the sample data, SVM is used. Fuzzy C-means addresses the problem of calculation complexity by performing clustering on sample data. The suggested FCMTSR improves precision by 2% while reducing training time by 55%. Gharghan et al. [156] proposed an LNSM channel model and PSO-ANN method-based approach. This approach is based on the distance calculation among mobile and static nodes. Equation (60) calculates the distance between these mobile and static nodes:

$$RSSI(dBm) = P_t(dBm) - PL(d)dBm \tag{59}$$

So-in et al. [157] compared various machine learning strategies for improving localization accuracy and computational complexity. FL, GA, NN, and SVM are the ML algorithms chosen for the analytical approach. This approach is able to train the data-set comparatively fast manner. Following that, MG-ELM is used to lessen the localization error. If and only if the MSO’s energy (E) is low, the new estimated location will be updated:

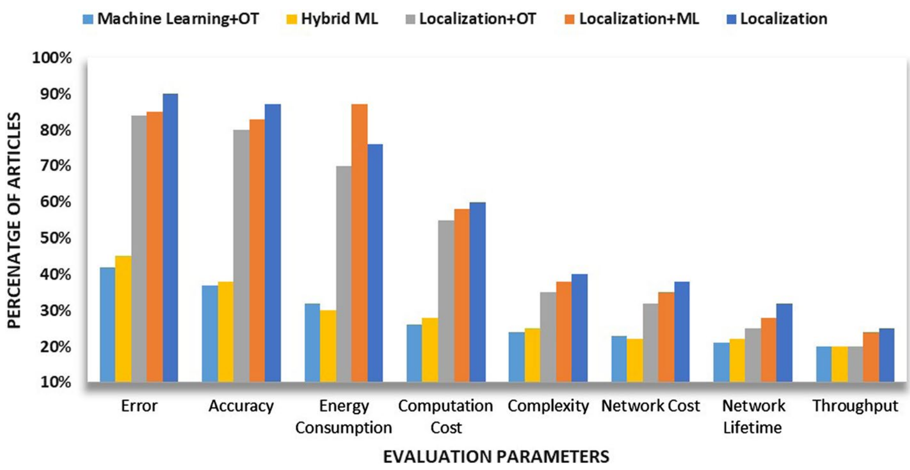


Fig. 12 Percentage of Articles for Various Evaluation Parameters

$$E(S_j) = \sum_{neighbourS[k]} (dist\_est(S[j], S[k] - r) \tag{60}$$

Bernas et al. [158] proposed an algorithm based on "k-means" and "fuzzy c-means" ML technique. This algorithm based on the feature of separating the network field to improves the localization accuracy. The coordinates are calculated as follow when k-NN is implemented:

$$x = \frac{\sum_{s=1}^{k} (x_{j_s} / \|\mathrm{r} - \mathrm{p}_{j_s}\|)}{\sum_{s=1}^{k} 1/\|\mathrm{r} - \mathrm{p}_{j_s}\|} \tag{61}$$

The coordinates are calculated as follow when fuzzy c-means is implemented"

$$x = \sum_{s=1}^{k} x_{j_s} u_{j_s}(\mathrm{r}) \tag{62}$$

Payal et al. [159] used the simple path loss model shown below is employed by incorporating "FFANN" model:

$$PL(d)(db) = \overline{PL}(d_0) + 10\eta \log\left(\frac{d}{d_0}\right) + X_\sigma \tag{63}$$

The above literature survey analyses the various articles in which localization algorithms have been implemented using machine learning, hybrid machine learning and optimization techniques. There exist few articles in which both the techniques or hybrid ML techniques are implemented. According to the above literature review, when localization techniques are used with hybrid ML or ML with optimization approaches, they outperform on numerous parameters. While when solely used or used only with ML or only with optimization technique they can conquer only one or two parameters like error or energy efficiency. Figure 12 shows that the hybrid ML and Optimization Techniques with ML are least explored on various parameters.

5 Challenges to Implement Hybrid ML and Optimization Strategies for Localization

Based on the Above literature survey various challengers have been identified:

- *Limited Training Data* Obtaining labeled training data for machine learning algorithms in WSNs can be challenging due to resource constraints and the need for accurate ground truth data. Limited training data can hinder the performance and generalizability of machine learning models.
- *Scalability* WSNs often consist of a large number of sensors, leading to scalability challenges in machine learning and optimization-based localization. Designing algorithms that can handle the increasing number of sensors while maintaining accuracy and efficiency is a significant challenge.
- *Energy Efficiency* Energy is a critical resource in WSNs, and energy-efficient localization is essential to prolong the network's lifetime. Machine learning and optimization algorithms should be designed to minimize energy consumption during the localization process, considering the limited battery capacity of sensor nodes.
- *Localization Accuracy* Achieving high localization accuracy in WSNs is challenging due to factors such as signal attenuation, multipath interference, and environmental conditions. Overcoming these challenges and improving localization accuracy remains a research focus.
- *Dynamic Environments* WSNs operate in dynamic environments where sensor nodes may move or be deployed in changing conditions. Machine learning and optimization algorithms should be able to adapt to dynamic environments and provide accurate localization despite changes in the network topology or physical surroundings.
- *Robustness to Sensor Failures and Malicious Attacks* WSNs are susceptible to sensor failures and malicious attacks that can compromise localization accuracy and integrity. Developing robust algorithms that can handle sensor failures, localization outliers, and secure localization against attacks is a significant research challenge.
- *Real-Time Localization* Real-time localization is crucial for many WSN applications. Machine learning and optimization-based approaches should be designed to provide timely localization results while considering the computational and communication constraints of the network.
- *Localization in Sparse Networks* In some scenarios, WSNs may have sparse node deployments, leading to challenges in accurate localization. Designing algorithms that can handle sparse networks and leverage limited connectivity information to achieve accurate localization poses a research challenge.
- *Trade-off between Localization Accuracy and Complexity* There is often a trade-off between localization accuracy and the complexity of machine learning and optimization algorithms. Balancing the accuracy and complexity to achieve an optimal solution is a challenge in WSN localization.
- *Real-World Validation and Deployment* Validating and deploying ML and OT in real-world WSN deployments can be challenging due to the variability of environments, system constraints, and the need for extensive testing and evaluation.

Addressing these research challenges will contribute to develop comparatively more robust, accurate, and efficient machine learning and optimization-based localization approaches for WSNs, enabling their widespread adoption in various applications.

6 Conclusion

In this research, our objective is to provide insights into the utilization of ML and optimization techniques to address localization challenges. To achieve this, we have organized the study into four main sections. The first section introduces the motivation behind our research and outlines the flow of the article. In the next section, we identified and elaborated existing research gaps and obstacles in localization preceded by Sect. 3 which is divided into three subsections. First subsection provides a comprehensive overview of localization by highlights the difficulties encountered during the localization phase. Second subsection focuses on ML strategies applied to the localization problem, while third subsection elaborates optimization strategies for localization. Lastly, in fourth section, we present comparative tables based on a literature review, allowing for a comprehensive comparison of localization, ML and OT.

To enhance the depth of our survey, we have reviewed and incorporated findings from three analytical surveys that introduce novel approaches in the field. Our analysis concludes that there is still limited utilization of Hybrid Techniques, which combine optimized localization with machine learning. Additionally, we provide a summary of the comparison tables, laying the groundwork for future research in WSN localization. Further investigations can focus on exploring additional optimization-based ML methods, particularly for live applications involving IoT devices in various domains such as agriculture, defense, and medicine.

7 Future Scope

The future directions to develop localization techniques in WSNs using machine learning and optimization involves several potential avenues for research and development. Here are some future directions to consider:

- *Transfer Learning* Investigate TL techniques to address the challenge during localization of nodes in different environments or scenarios. By training models on labelled data from one WSN deployment and transferring the learned knowledge to a new deployment, it may be possible to reduce the need for extensive calibration or training data collection.
- *Cooperative Localization* Explore cooperative localization techniques where neighbouring sensor nodes collaborate to improve localization accuracy. Machine learning and optimization algorithms can be employed to design efficient collaboration strategies, data fusion techniques, or distributed optimization algorithms for cooperative localization.
- *Sensor Selection and Placement* Investigate machine learning and optimization approaches for optimal sensor selection and placement in WSNs. By strategically selecting and placing sensors in the network, it is possible to improve localization accuracy and reduce resource consumption. Techniques such as reinforcement learning or genetic algorithms can be explored to optimize sensor selection and placement strategies.
- *Real-Time and Dynamic Localization* Develop real-time and dynamic localization techniques that can adapt to changing environmental conditions, mobility of nodes, or net-

work dynamics. Machine learning algorithms can be trained to adaptively learn and update localization models based on the evolving sensor data, enabling accurate and robust localization in dynamic WSN scenarios.
- *Experimental Validation and Benchmarking* Conduct extensive experimental validations and benchmarking of the proposed localization techniques using real-world WSN deployments. Compare the performance of different machine learning and optimization-based approaches under varying conditions, network sizes, environmental factors, and mobility patterns to provide practical insights and guidelines for their adoption.

These future directions can contribute to the advancement of localization techniques in WSNs by harnessing the power of machine learning and optimization, improving accuracy, efficiency, scalability, and adaptability to diverse deployment scenarios and application requirements.

Acknowledgements I am currently pursuing my doctoral studies at IIT Roorkee in India, under the QIP fellowship program sponsored by M.J.P. Rohilkhand University, Bareilly. The research presented in this paper is an integral part of my doctoral work. I would like to express my sincere gratitude to my supervisor, Prof. Subhash Chander Sharma, from IIT Roorkee, for his invaluable support and guidance. Throughout my academic journey, Prof. Sharma's unwavering enthusiasm, extensive knowledge, and meticulous attention to detail have been a constant source of inspiration. From my initial exploration of numerous books to the finalization of this research paper, his mentorship has played a pivotal role in shaping the current form of this work.

Funding No funding information is provided as the research work did not require any external financial support.

Data Availability Data sharing is not applicable to this article as this is a survey paper and no datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare that no financial or non-financial ties to the subject matter or materials are covered in this paper. Honoraria, educational grants, membership in speaker bureaus, employment, consultancies, stock ownership, expert testimony, patent-licensing deals, and personal or professional relationships, opinions, affiliations, or knowledge are all examples of compensation.

References

1. Potdar, V., Sharif, A., & Chang, E. (2009). Wireless sensor networks: A survey. In *Proceedings—International Conference on Advanced Information Networking and Applications, AINA* (pp. 636–641). https://doi.org/10.1109/WAINA.2009.192.
2. Zhou, Z., Xu, J., Zhang, Z., Lei, F., & Fang, W. (2017). Energy-efficient optimization for concurrent compositions of WSN services. *IEEE Access, 5*, 19994–20008. https://doi.org/10.1109/ACCESS.2017.2752756
3. Yadav, P., Kumar, K., & Sharma, S.C. (2023). Machine learning based techniques for node localization in WSN: A survey. In *Proceedings—IEEE International Conference on Device Intelligence, Computing and Communication Technologies, DICCT 2023* (pp. 12–17).https://doi.org/10.1109/DICCT56244.2023.10110235.
4. Alrajeh, N.A., Bashir, M., & Shams, B. (2013). Localization techniques in wireless sensor networks, vol. 2013. https://doi.org/10.1155/2013/304628.
5. Kim, T., Vecchietti, L. F., Choi, K., Lee, S., & Har, D. (2021). Machine learning for advanced wireless sensor networks: A review. *IEEE Sensors Journal, 21*(11), 12379–12397. https://doi.org/10.1109/JSEN.2020.3035846

6. Cheng, Y.K., Chang, R.Y., & Chen, L.J. (2017). A comparative study of machine-learning indoor localization using FM and DVB-T signals in real testbed environments. In *IEEE Vehicular Technology Conference*, vol. 2017. https://doi.org/10.1109/VTCSPRING.2017.8108573.
7. Yang, Q. (2022). A new localization method based on improved particle swarm optimization for wireless sensor networks. *IET Software, 16*(3), 251–258. https://doi.org/10.1049/SFW2.12027
8. Sobehy, A., Renault, É., & Mühlethaler, P. (2022). Generalization aspect of accurate machine learning models for CSI-based localization. *Annales des Telecommunications/Annals of Telecommunications, 77*(5–6), 345–357. https://doi.org/10.1007/S12243-021-00853-Z/TABLES/3
9. Turgut, Z., Ustebay, S., Ali Aydın, M., Gürkaş Aydın, G. Z., & Sertbaş, A. (2019). Performance analysis of machine learning and deep learning classification methods for indoor localization in Internet of Things environment. *Transactions on Emerging Telecommunications Technologies, 30*(9), e3705. https://doi.org/10.1002/ETT.3705
10. Bai, J., Sun, Y., Meng, W., & Li, C. (2021). Wi-Fi fingerprint-based indoor mobile user localization using deep learning. *Wireless Communications and Mobile Computing, 2021*, 1–12. https://doi.org/10.1155/2021/6660990
11. Eder, M., Reip, M., & Steinbauer, G. (2022). Creating a robot localization monitor using particle filter and machine learning approaches. *Applied Intelligence, 52*(6), 6955–6969. https://doi.org/10.1007/S10489-020-02157-6/TABLES/7
12. Cottone, P., Gaglio, S., Lo Re, G., & Ortolani, M. (2016). A machine learning approach for user localization exploiting connectivity data. *Engineering Applications of Artificial Intelligence, 50*, 125–134. https://doi.org/10.1016/J.ENGAPPAI.2015.12.015
13. Stanoev, A., Filiposka, S., In, V., & Kocarev, L. (2016). Cooperative method for wireless sensor network localization. *Ad Hoc Networks, 40*, 61–72. https://doi.org/10.1016/J.ADHOC.2016.01.003
14. Ghari, P. M., Shahbazian, R., & Ghorashi, S. A. (2016). Wireless sensor network localization in harsh environments using SDP relaxation. *IEEE Communications Letters, 20*(1), 137–140. https://doi.org/10.1109/LCOMM.2015.2498179
15. Miao, Y., Wu, H., & Zhang, L. (2018). The accurate location estimation of sensor node using received signal strength measurements in large-scale farmland. *Journal of Sensors, 2018*, 1–10. https://doi.org/10.1155/2018/2325863
16. Sivasakthiselvan, S., & Nagarajan, V. (2020). Localization techniques of wireless sensor networks: A review. In *Proceedings of the 2020 IEEE International Conference on Communication and Signal Processing, ICCSP 2020* (pp. 1643–1648). https://doi.org/10.1109/ICCSP48568.2020.9182290.
17. More, A., & Raisinghani, V. (2017). A survey on energy efficient coverage protocols in wireless sensor networks. *Journal of King Saud University—Computer and Information Sciences, 29*(4), 428–448. https://doi.org/10.1016/J.JKSUCI.2016.08.001
18. Jinning, Z., et al. (2019). A modified KNN Indoor WiFi localization method With K-median cluster. *IOP Conference Series: Materials Science and Engineering, 608*(1), 012008. https://doi.org/10.1088/1757-899X/608/1/012008
19. Mao, G., & Fidan, B. (2009). Localization algorithms and strategies for wireless sensor networks. In *Localization Algorithms and Strategies for Wireless Sensor Networks* (pp. 1–510). https://doi.org/10.4018/978-1-60566-396-8.
20. Cheng, L., Maple, C., Wu, C., & Meng, W. (2013). Localization in wireless sensor network. *International Journal of Distributed Sensor Networks, 9*, 457874. https://doi.org/10.1155/2013/457874
21. Meng, W., Xiao, W., & Xie, L. (2011). An efficient EM algorithm for energy-based multisource localization in wireless sensor networks. *IEEE Transactions on Instrumentation and Measurement, 60*(3), 1017–1027. https://doi.org/10.1109/TIM.2010.2047035
22. Pal, A. (2010). Localization algorithms in wireless sensor networks: Current approaches and future challenges. *Network Protocols and Algorithms, 2*(1), 45–73. https://doi.org/10.5296/NPA.V2I1.279
23. Tiwari, A., & Kumar, M. (2021). A review of range based localization techniques in wireless sensor networks. *SSRG International Journal of Electronics and Communication Engineering, 8*, 1–5. https://doi.org/10.14445/23488549/IJECE-V8I12P101
24. Ristic, B., Morelande, M., Farina, A., & Dulman, S. (2006). On proximity-based range-free node localisation in wireless sensor networks. In *2006 9th International Conference on Information Fusion*, 2006, Accessed: May 19, 2023. [Online]. Available: https://www.academia.edu/2755194/On_proximity_based_range_free_node_localisation_in_wireless_sensor_networks.
25. Suo, H., Wan, J., Huang, L., & Zou, C. (2012). Issues and challenges of wireless sensor networks localization in emerging applications. In *Proceedings—2012 International Conference on Computer Science and Electronics Engineering, ICCSEE 2012*, *3*, 447–451. https://doi.org/10.1109/ICCSEE.2012.44.

26. Jondhale, S. R., Deshpande, R. S., Walke, S. M., & Jondhale, A. S. (2017). Issues and challenges in RSSI based target localization and tracking in wireless sensor networks. *International Conference on Automatic Control and Dynamic Optimization Techniques, ICACDOT, 2016*, 594–598. https://doi.org/10.1109/ICACDOT.2016.7877655
27. Majid, M., et al. (2022). Applications of wireless sensor networks and Internet of Things frameworks in the industry revolution 4.0: A systematic literature review. *Sensors, 22*(6), 2087. https://doi.org/10.3390/S22062087
28. Chelouah, L., Semchedine, F., & Bouallouche-Medjkoune, L. (2018). Localization protocols for mobile wireless sensor networks: A survey. *Computers & Electrical Engineering, 71*, 733–751. https://doi.org/10.1016/J.COMPELECENG.2017.03.024
29. Ullah, I., Liu, Y., Su, X., & Kim, P. (2019). Efficient and accurate target localization in underwater environment. *IEEE Access, 7*, 101415–101426. https://doi.org/10.1109/ACCESS.2019.2930735
30. Kuo, S. P., Kuo, H. J., & Tseng, Y. C. (2009). The beacon movement detection problem in wireless sensor networks for localization applications. *IEEE Transactions on Mobile Computing, 8*(10), 1326–1338. https://doi.org/10.1109/TMC.2009.15
31. Jiang, C., Li, T. S., Bin Liang, J., & Wu, H. (2017). Low-latency and energy-efficient data preservation mechanism in low-duty-cycle sensor networks. *Sensors, 17*(5), 1051. https://doi.org/10.3390/S17051051
32. Liu, X., Gao, L., Lu, J., & Lioliou, E. (2016). Environmental risks, localization and the overseas subsidiary performance of MNEs from an emerging economy. *Journal of World Business, 51*(3), 356–368. https://doi.org/10.1016/J.JWB.2015.05.002
33. Nemer, I., Sheltami, T., Shakshuki, E., Elkhail, A. A., & Adam, M. (2021). Performance evaluation of range-free localization algorithms for wireless sensor networks. *Personal and Ubiquitous Computing, 25*(1), 177–203. https://doi.org/10.1007/S00779-020-01370-X
34. Yadav, P., Sharma, S. C., Singh, O., & Rishiwal, V. (2023). Optimized localization learning algorithm for indoor and outdoor localization system in WSNs. *Wireless Personal Communications, 130*(1), 651–672. https://doi.org/10.1007/S11277-023-10304-8/FIGURES/9
35. Xie, N., Chen, Y., Li, Z., & Wu, D. O. (2021). Lightweight secure localization approach in wireless sensor networks. *IEEE Transactions on Communications, 69*(10), 6879–6893. https://doi.org/10.1109/TCOMM.2021.3098794
36. Ou, C. H., & Ssu, K. F. (2008). Sensor position determination with flying anchors in three-dimensional wireless sensor networks. *IEEE Transactions on Mobile Computing, 7*(9), 1084–1097. https://doi.org/10.1109/TMC.2008.39
37. Yadav, P., & Sharma, S.C. (2023). Q-Learning based optimized localization in WSN. In *2023 6th International Conference on Information Systems and Computer Networks (ISCON)* (pp. 1–5). https://doi.org/10.1109/ISCON57294.2023.10112130.
38. Alsheikh, M.A., Lin, S., Niyato, D., & Tan, H.-P. (2015). Machine learning in wireless sensor networks: algorithms, strategies, and applications.
39. Chen, Q., Chen, Y., Fan, C., Yang, F., & Wang, P. (2012). Research on node localization algorithm in WSN basing machine learning. https://doi.org/10.2991/ICCIA.2012.10.
40. Wang, L., Er, M. J., & Zhang, S. (2020). A kernel extreme learning machines algorithm for node localization in wireless sensor networks. *IEEE Communications Letters, 24*(7), 1433–1436. https://doi.org/10.1109/LCOMM.2020.2986676
41. Robinson, Y. H., Vimal, S., Julie, E. G., Lakshmi Narayanan, K., & Rho, S. (2022). 3-Dimensional manifold and machine learning based localization algorithm for wireless sensor networks. *Wireless Personal Communications, 127*(1), 523–541. https://doi.org/10.1007/S11277-021-08291-9/FIGURES/10
42. Cheng, L., Wu, X., & Wang, Y. (2017). A non-line of sight localization method based on k-means clustering algorithm. In *Proceedings of 2017 IEEE 7th International Conference on Electronics Information and Emergency Communication, ICEIEC 2017* (pp. 465–468). https://doi.org/10.1109/ICEIEC.2017.8076606.
43. Chriki, A., Touati, H., & Snoussi, H. (2017). SVM-based indoor localization in wireless sensor networks. *2017 13th International Wireless Communications and Mobile Computing Conference, IWCMC, 2017*, 1144–1149. https://doi.org/10.1109/IWCMC.2017.7986446
44. Mohammed, S. K., Singh, S., Mizouni, R., & Otrok, H. (2023). A deep learning framework for target localization in error-prone environment. *Internet of Things, 22*, 100713. https://doi.org/10.1016/J.IOT.2023.100713
45. Morelande, M.R., Moran, B., & Brazil, M. (2008). Bayesian node localisation in wireless sensor networks. In *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing—Proceedings* (pp. 2545–2548). https://doi.org/10.1109/ICASSP.2008.4518167.

46. (15) (PDF) NLOS Identification for Indoor Localization using Random Forest Algorithm. https://www.researchgate.net/publication/330901602_NLOS_Identification_for_Indoor_Localization_using_Random_Forest_Algorithm (Accessed May 19, 2023).
47. Zhu, X. (2020). Indoor localization based on optimized KNN. *Network and Communication Technologies, 5*(2), 34. https://doi.org/10.5539/NCT.V5N2P34
48. Kumar, S., Tiwari, S. N., & Hegde, R. M. (2015). Sensor node tracking using semi-supervised hidden Markov models. *Ad Hoc Networks, 33*, 55–70. https://doi.org/10.1016/J.ADHOC.2015.04.004
49. Yoo, J.H., Kim, W., & Kim, H.J. (2011). Event-driven Gaussian process for object localization in wireless sensor networks (pp. 2790–2795) https://doi.org/10.1109/IROS.2011.6094804.
50. Poulose, A., & Han, D.S. (2021). Feature-based deep LSTM network for indoor localization using UWB measurements. In *3rd International Conference on Artificial Intelligence in Information and Communication, ICAIIC 2021* (pp. 298–301). https://doi.org/10.1109/ICAIIC51459.2021.9415277.
51. Yan, W., Jin, D., Lin, Z., & Yin, F. (2021). Graph neural network for large-scale network localization,. In *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing—Proceedings*, *2021*, 5250–5254. https://doi.org/10.1109/ICASSP39728.2021.9414520.
52. Tang, Z., et al. (2015). CTLL: A cell-based transfer learning method for localization in large scale wireless sensor networks. *International Journal of Distributed Sensor Networks., 11*, 252653. https://doi.org/10.1155/2015/252653
53. Khelifi, M., & Moussaoui, S. (2021). ReLM: An efficient reinforcement learning-based localization algorithm for mobile wireless sensor networks. In *2021 International Conference on Innovations in Intelligent Systems and Applications, INISTA 2021: Proceedings*. https://doi.org/10.1109/INISTA52262.2021.9548531.
54. Tripathy, P., & Khilar, P. M. (2022). An ensemble approach for improving localization accuracy in wireless sensor network. *Computer Networks, 219*, 109427. https://doi.org/10.1016/J.COMNET.2022.109427
55. Behera, A. P., Singh, A., Verma, S., & Kumar, M. (2020). Manifold learning with localized procrustes analysis based WSN localization. *IEEE Sensors Letters, 4*(10), 1–4. https://doi.org/10.1109/LSENS.2020.3025360
56. Jain, N., Verma, S., & Kumar, M. (2017). Incremental LLE for localization in sensor networks. *IEEE Sensors Journal, 17*(19), 6483–6492. https://doi.org/10.1109/JSEN.2017.2738704
57. Kar, A. K. (2016). Bio inspired computing: A review of algorithms and scope of applications. *Expert Systems with Applications, 59*, 20–32. https://doi.org/10.1016/J.ESWA.2016.04.018
58. Kulkarni, R. V., & Venayagamoorthy, G. K. (2010). Bio-inspired algorithms for autonomous deployment and localization of sensor nodes. *IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews, 40*(6), 663–675. https://doi.org/10.1109/TSMCC.2010.2049649
59. Alomari, A., Phillips, W., Aslam, N., & Comeau, F. (2017). Swarm intelligence optimization techniques for obstacle-avoidance mobility-assisted localization in wireless sensor networks. *IEEE Access, 6*, 22368–22385. https://doi.org/10.1109/ACCESS.2017.2787140
60. Liu, X., & You, X. (2021). Node localization algorithm based on improved DV-Hop wireless sensor network. In *2021 5th CAA International Conference on Vehicular Control and Intelligence, CVCI 2021*. https://doi.org/10.1109/CVCI54083.2021.9661258.
61. Hao, Z., Li, X., & Ding, Y. (2018). An improved PSO algorithm for node localization in indoor long-narrow confined space. In *Proceedings of the 13th IEEE Conference on Industrial Electronics and Applications, ICIEA 2018* (pp. 1841–1846). https://doi.org/10.1109/ICIEA.2018.8398008.
62. Shen, S., Sun, L., Dang, Y., Zou, Z., & Wang, R. (2018). Node localization based on improved PSO and mobile nodes for environmental monitoring WSNs. *International Journal of Wireless Information Networks, 25*(4), 470–479. https://doi.org/10.1007/S10776-018-0414-3/FIGURES/9
63. Saha, S., Saha, A., Roy, B., Sarkar, R., Bhardwaj, D., & Kundu, B. (2022). Integrating the particle swarm optimization (PSO) with machine learning methods for improving the accuracy of the landslide susceptibility model. *Earth Science Informatics, 15*(4), 2637–2662. https://doi.org/10.1007/S12145-022-00878-5/TABLES/3
64. Lee, S. H., et al. (2023). PSO-based target localization and tracking in wireless sensor networks. *Electronics, 12*(4), 905. https://doi.org/10.3390/ELECTRONICS12040905
65. Nithya, B., & Jeyachidra, J. (2021). Hybrid ABC-BAT optimization algorithm for localization in HWSN. *Microprocessors and Microsystems*. https://doi.org/10.1016/J.MICPRO.2021.104024
66. Goyal, S., & Patterh, M. S. (2016). Modified bat algorithm for localization of wireless sensor network. *Wireless Personal Communications, 86*(2), 657–670. https://doi.org/10.1007/S11277-015-2950-9/TABLES/5
67. Nithya, B., & Jeyachidra, J. (2021). Optimized anchor based localization using bat optimization algorithm for heterogeneous WSN. In *Proceedings of the 2021 IEEE International Conference on*

Innovative Computing, Intelligent Communication and Smart Electrical Systems, ICSES 2021. https://doi.org/10.1109/ICSES52305.2021.9633947.

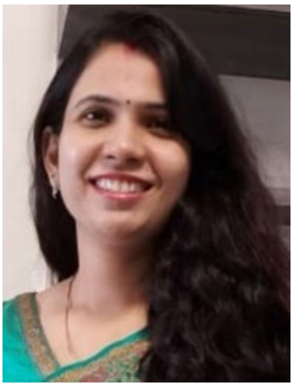
68. Yu, S., Zhu, J., & Lv, C. (2023). A quantum annealing bat algorithm for node localization in wireless sensor networks. *Sensors (Basel), 23*(2), 782. https://doi.org/10.3390/S23020782
69. Mihoubi, M., Rahmoun, A., Lorenz, P., & Lasla, N. (2018). An effective Bat algorithm for node localization in distributed wireless sensor network. *Security and Privacy, 1*(1), e7.
70. Yang, Y., Sun, L., & Xiang, M. (2015). Range-free localization algorithm based on mass spring model for wireless sensor networks. *Chinese Journal of Sensors and Actuators, 28*(6), 914–919. https://doi.org/10.3969/J.ISSN.1004-1699.2015.06.023
71. Oliva, G., Setola, R., Panzieri, S., & Pascucci, F. (2016). Localization of networks with presence and distance constraints based on 1-hop and 2-hop mass–spring optimization. *ICT Express, 2*(1), 19–22. https://doi.org/10.1016/J.ICTE.2016.02.005
72. Arora, S., & Singh, S. (2019). Butterfly optimization algorithm: A novel approach for global optimization. *Soft Computing, 23*(3), 715–734. https://doi.org/10.1007/S00500-018-3102-4/FIGURES/10
73. Arora, S., & Anand, P. (2019). Learning automata-based butterfly optimization algorithm for engineering design problems. *International Journal of Computational Materials Science and Engineering, 7*(4), 1850021. https://doi.org/10.1142/S2047684118500215
74. Stromberger, I., Tuba, E., Bacanin, N., Beko, M., & Tuba, M. (2018). Monarch butterfly optimization algorithm for localization in wireless sensor networks. In *2018 28th International Conference Radioelektronika, RADIOELEKTRONIKA* (pp. 1–6). https://doi.org/10.1109/RADIOELEK.2018.8376387.
75. Arora, S., & Singh, S. (2017). Node localization in wireless sensor networks using butterfly optimization algorithm. *Arabian Journal for Science and Engineering, 42*(8), 3325–3335. https://doi.org/10.1007/S13369-017-2471-9/METRICS
76. Makhadmeh, S. N., et al. (2023). Recent advances in butterfly optimization algorithm, its versions and applications. *Archives of Computational Methods in Engineering, 30*(2), 1399–1420. https://doi.org/10.1007/S11831-022-09843-3/TABLES/2
77. Kaur, S., et al. (2023). Node localization and data aggregation scheme using cuckoo search and neural network. *Expert Systems, 40*(4), e13033. https://doi.org/10.1111/EXSY.13033
78. Kotiyal, V., Singh, A., Sharma, S., Nagar, J., & Lee, C. C. (2021). ECS-NL: An enhanced cuckoo search algorithm for node localisation in wireless sensor networks. *Sensors., 21*(11), 3576. https://doi.org/10.3390/S21113576
79. Cheng, J., & Xia, L. (2016). An effective cuckoo search algorithm for node localization in wireless sensor network. Sensors (Switzerland), *16(9)*. https://doi.org/10.3390/S16091390.
80. Cheng, J., & Xia, L. (2016). An effective cuckoo search algorithm for node localization in wireless sensor network. *Sensors, 16*(9), 1390. https://doi.org/10.3390/S16091390
81. Shenkai, G., Li, C., Jing, W., & Xianglong, L. (2021). An improved approach for iterative nodes localization by using artificial bee colony, p. 109. https://doi.org/10.1117/12.2615329.
82. Shan, H. M. (2021). A node localisation method for wireless sensor networks based on an improved bee colony algorithm. *International Journal of Sensor Networks, 36*(2), 108–114. https://doi.org/10.1504/IJSNET.2021.115922
83. Annepu, V., & Rajesh, A. (2020). Implementation of an efficient artificial bee colony algorithm for node localization in unmanned aerial vehicle assisted wireless sensor networks. *Wireless Personal Communications, 114*(3), 2663–2680. https://doi.org/10.1007/S11277-020-07496-8/FIGURES/11
84. Krishnamoorthy, V. K., Duraisamy, U. N., Jondhale, A. S., Lloret, J., & Ramasamy, B. V. (2023). Energy-constrained target localization scheme for wireless sensor networks using radial basis function neural network. *International Journal of Distributed Sensor Networks, 2023*, 1–12. https://doi.org/10.1155/2023/1426430
85. Mohar, S. S., Goyal, S., & Kaur, R. (2022). Localization of sensor nodes in wireless sensor networks using bat optimization algorithm with enhanced exploration and exploitation characteristics. *Journal of Supercomputing, 78*(9), 11975–12023. https://doi.org/10.1007/S11227-022-04320-X/TABLES/8
86. Zazali, A. A., Subramaniam, S. K., & Zukarnain, Z. A. (2020). Flood control distance vector-hop (FCDV-Hop) localization in wireless sensor networks. *IEEE Access, 8*, 206592–206613. https://doi.org/10.1109/ACCESS.2020.3038047
87. Han, G., Zhang, C., Jiang, J., Yang, X., & Guizani, M. (2017). Mobile anchor nodes path planning algorithms using network-density-based clustering in wireless sensor networks. *Journal of Network and Computer Applications, 85*, 64–75. https://doi.org/10.1016/J.JNCA.2016.12.016
88. Kouroshnezhad, S., Peiravi, A., Sayad Haghighi, M., & Zhang, Q. (2019). A mixed-integer linear programming approach for energy-constrained mobile anchor path planning in wireless sensor networks localization. *Ad Hoc Networks, 87*, 188–199. https://doi.org/10.1016/J.ADHOC.2018.12.014

89. Karimi Alavijeh, A., Ramezani, M. H., & Karimi Alavijeh, A. (2018). Localization improvement in wireless sensor networks using a new statistical channel model. *Sensors and Actuators A: Physical, 271*, 283–289. https://doi.org/10.1016/J.SNA.2018.01.015
90. Chen, Y., Lu, S., Chen, J., & Ren, T. (2017). Node localization algorithm of wireless sensor networks with mobile beacon node. *Peer-to-Peer Networking and Applications, 10*(3), 795–807. https://doi.org/10.1007/S12083-016-0522-8
91. Zhang, S., Er, M. J., Zhang, B., & Naderahmadian, Y. (2017). A novel heuristic algorithm for node localization in anisotropic wireless sensor networks with holes. *Signal Processing, 138*, 27–34. https://doi.org/10.1016/J.SIGPRO.2017.03.010
92. Shahzad, F., Sheltami, T. R., & Shakshuki, E. M. (2017). DV-maxHop: A fast and accurate range-free localization algorithm for anisotropic wireless networks. *IEEE Transactions on Mobile Computing, 16*(9), 2494–2505. https://doi.org/10.1109/TMC.2016.2632715
93. Tomic, S., Beko, M., & Dinis, R. (2017). 3-D target localization in wireless sensor networks using RSS and AoA measurements. *IEEE Transactions on Vehicular Technology, 66*(4), 3197–3210. https://doi.org/10.1109/TVT.2016.2589923
94. Lv, T., Gao, H., Li, X., Yang, S., & Hanzo, L. (2016). Space-time hierarchical-graph based cooperative localization in wireless sensor networks. *IEEE Transactions on Signal Processing, 64*(2), 322–334. https://doi.org/10.1109/TSP.2015.2480038
95. Li, S., Wang, X., Zhao, S., Wang, J., & Li, L. (2013). Local semidefinite programming-based node localization system for wireless sensor network applications. *IEEE Systems Journal, 8*(3), 879–888. https://doi.org/10.1109/JSYST.2013.2260625
96. Ou, C. H., & He, W. L. (2013). Path planning algorithm for mobile anchor-based localization in wireless sensor networks. *IEEE Sensors Journal, 13*(2), 466–475. https://doi.org/10.1109/JSEN.2012.2218100
97. Zhao, J., et al. (2013). Localization of wireless sensor networks in the wild: Pursuit of ranging quality. *IEEE/ACM Transactions on Networking, 21*(1), 311–323. https://doi.org/10.1109/TNET.2012.2200906
98. Chang, C. Y., Lin, C. Y., & Chang, C. T. (2012). Tone-based localization for distinguishing relative locations in wireless sensor networks. *IEEE Sensors Journal, 12*(5), 1058–1070. https://doi.org/10.1109/JSEN.2011.2163503
99. Abdelhakim, A. Machine learning for localization of radioactive sources via a distributed sensor network. https://doi.org/10.1007/s00500-023-08447-8.
100. Asif, R., Farooq-i-Azam, M., Chaudary, M. H., Husen, A., & Hassan, S. R. (2023). A distance vector hop-based secure and robust localization algorithm for wireless sensor networks. *Electronics, 12*(10), 2237. https://doi.org/10.3390/ELECTRONICS12102237
101. Abdullah, O.A., Al-Hraishawi, H., & Chatzinotas S. (2023). Deep learning-based device-free localization in wireless sensor networks. In *2023 IEEE Wireless Communications and Networking Conference (WCNC)* (pp. 1–6). https://doi.org/10.1109/WCNC55385.2023.10118744.
102. Kagi, S., & Mathapati, B. S. (2022). Localization in wireless sensor network using machine learning optimal trained deep neural network by parametric analysis. *Measurement: Sensors, 24*, 100427. https://doi.org/10.1016/J.MEASEN.2022.100427
103. Gang, Q., Muhammad, A., Khan, Z. U., Khan, M. S., Ahmed, F., & Ahmad, J. (2022). Machine learning-based prediction of node localization accuracy in IIoT-based MI-UWSNs and design of a TD coil for omnidirectional communication. *Sustainability, 14*(15), 1–23.
104. Liouane, O., Femmam, S., Bakir, T., & Ben Abdelali, A. (2021). Improved two hidden layers extreme learning machines for node localization in range free wireless sensor networks. *Journal of Communications., 16*(12), 528–534. https://doi.org/10.12720/JCM.16.12.528-534
105. Hu, Q., Wu, F., Wong, R. K., Millham, R. C., & Fiaidhi, J. (2023). A novel indoor localization system using machine learning based on bluetooth low energy with cloud computing. *Computing, 105*(3), 689–715. https://doi.org/10.1007/S00607-020-00897-4/TABLES/3
106. Al-Rashdan, W. Y., & Tahat, A. (2020). A comparative performance evaluation of machine learning algorithms for fingerprinting based localization in DM-MIMO wireless systems relying on big data techniques. *IEEE Access, 8*, 109522–109534. https://doi.org/10.1109/ACCESS.2020.3001912
107. Kangyong, Y., Guo, W., Peng, T., Liu, Y., Zuo, P., & Wang, W. Parametric sparse bayesian dictionary learning for multiple sources localization with propagation parameters uncertainty and nonuniform noise.
108. Maghdid, H.S., Ghafoor, K.Z., Al-Talabani, A., Sadiq, A.S., Singh, P.K., & Rawat, D.B. (2022). Enabling accurate indoor localization for different platforms for smart cities using a transfer learning algorithm. *Internet Technology Letters*, *5(1)*. https://doi.org/10.1002/ITL2.200.

109. Bhatti, M. A., Riaz, R., Rizvi, S. S., Shokat, S., Riaz, F., & Kwon, S. J. (2020). Outlier detection in indoor localization and Internet of Things (IoT) using machine learning. *Journal of Communications and Networks, 22*(3), 236–243. https://doi.org/10.1109/JCN.2020.000018
110. Kim, M., Han, D., & Kevin Rhee, J. K. (2020). Machine learning for practical localization system using multiview CSI. *IEEE Access, 8*, 184575–184584. https://doi.org/10.1109/ACCESS.2020.3029598
111. Li, W., Chen, P., Wang, B., & Xie, C. (2019). Automatic localization and count of agricultural crop pests based on an improved deep learning pipeline. *Scientific Reports 9(1)*. https://doi.org/10.1038/S41598-019-43171-0.
112. Fan, J., & Awan, A. S. (2019). Non-line-of-sight identification based on unsupervised machine learning in ultra wideband systems. *IEEE Access, 7*, 32464–32471. https://doi.org/10.1109/ACCESS.2019.2903236
113. Srinivasan, S. M., Truong-Huu, T., & Gurusamy, M. (2019). Machine learning-based link fault identification and localization in complex networks. *IEEE Internet of Things Journal, 6*(4), 6556–6566. https://doi.org/10.1109/JIOT.2019.2908019
114. Yan, J., Xu, Z., Luo, X., Chen, C., & Guan, X. (2019). Feedback-based target localization in underwater sensor networks: A multisensor fusion approach. *IEEE Transactions on Signal and Information Processing over Networks, 5*(1), 168–180. https://doi.org/10.1109/TSIPN.2018.2866335
115. Panayiotou, T., Chatzis, S. P., & Ellinas, G. (2018). Leveraging statistical machine learning to address failure localization in optical networks. *Journal of Optical Communications and Networking, 10*(3), 162–173. https://doi.org/10.1364/JOCN.10.000162
116. Berz, E. L., Tesch, D. A., & Hessel, F. P. (2018). Machine-learning-based system for multi-sensor 3D localisation of stationary objects. *IET Cyber-Physical Systems: Theory & Applications, 3*(2), 81–88. https://doi.org/10.1049/IET-CPS.2017.0067
117. Prasad, K. N. R. S. V., Hossain, E., & Bhargava, V. K. (2018). Machine learning methods for RSS-based user positioning in distributed massive MIMO. *IEEE Transactions on Wireless Communications, 17*(12), 8402–8417. https://doi.org/10.1109/TWC.2018.2876832
118. Silva Almeida, J., Bezerra Marinho, L., Mendes Souza, J. W., Assis, E. A., & Reboucas Filho, P. P. (2018). Localization system for autonomous mobile robots using machine learning methods and omnidirectional sonar. *IEEE Latin America Transactions, 16*(2), 368–374. https://doi.org/10.1109/TLA.2018.8327388
119. Amri, S., Khelifi, F., Bradai, A., Rachedi, A., Kaddachi, M. L., & Atri, M. (2019). A new fuzzy logic based node localization mechanism for wireless sensor networks. *Future Generation Computer Systems, 93*, 799–813. https://doi.org/10.1016/J.FUTURE.2017.10.023
120. Khatab, Z. E., Hajihoseini, A., & Ghorashi, S. A. (2018). A fingerprint method for indoor localization using autoencoder based deep extreme learning machine. *IEEE Sensors Letters, 2*(1), 1–4. https://doi.org/10.1109/LSENS.2017.2787651
121. Bin Tariq, O., Lazarescu, M. T., Iqbal, J., & Lavagno, L. (2017). Performance of machine learning classifiers for indoor person localization with capacitive sensors. *IEEE Access, 5*, 12913–12926. https://doi.org/10.1109/ACCESS.2017.2721538
122. Wang, J., Zhang, X., Gao, Q., Yue, H., & Wang, H. (2017). Device-free wireless localization and activity recognition: A deep learning approach. *IEEE Transactions on Vehicular Technology, 66*(7), 6258–6267. https://doi.org/10.1109/TVT.2016.2635161
123. Zheng, K., et al. (2017). Energy-efficient localization and tracking of mobile devices in wireless sensor networks. *IEEE Transactions on Vehicular Technology, 66*(3), 2714–2726. https://doi.org/10.1109/TVT.2016.2584104
124. Jiang, M., Lu, S., Sui, Q., Dong, H., Sai, Y., & Jia, L. (2015). Low velocity impact localization on CFRP based on FBG sensors and ELM algorithm. *IEEE Sensors Journal, 15*(8), 4451–4456. https://doi.org/10.1109/JSEN.2015.2422851
125. Kim, W., Park, J., & Kim, H. J. (2010). Target localization using ensemble support vector regression in wireless sensor networks. *IEEE Wireless Communications and Networking Conference, WCNC*. https://doi.org/10.1109/WCNC.2010.5506589
126. Rahman, M. S., Park, Y., & Kim, K. D. (2012). RSS-based indoor localization algorithm for wireless sensor network using generalized regression neural network. *Arabian Journal for Science and Engineering, 37*(4), 1043–1053. https://doi.org/10.1007/S13369-012-0218-1/METRICS
127. Wymeersch, H., Maranò, S., Gifford, W. M., & Win, M. Z. (2012). A machine learning approach to ranging error mitigation for UWB localization. *IEEE Transactions on Communications, 60*(6), 1719–1728. https://doi.org/10.1109/TCOMM.2012.042712.110035

128. Chadha, J., Jain, A., & Kumar, Y. (2023). Satellite imagery-based Airbus ship localization and detection using deep learning-based approaches. *Peer-to-Peer Networking and Applications*. https://doi.org/10.1007/S12083-023-01493-X
129. Klein, L. C., et al. (2023). A machine learning approach to robot localization using fiducial markers in RobotAtFactory 4.0 competition. *Sensors, 23*(6), 3128. https://doi.org/10.3390/S23063128
130. Al-Habashna, A., Wainer, G., & Aloqaily, M. (2022). Machine learning-based indoor localization and occupancy estimation using 5G ultra-dense networks. *Simulation Modelling Practice and Theory, 118*, 102543. https://doi.org/10.1016/J.SIMPAT.2022.102543
131. Mohanta, T. K., & Das, D. K. (2023). Improved wireless sensor network localization algorithm based on selective opposition class topper optimization (SOCTO). *Wireless Personal Communications, 128*(4), 2847–2868. https://doi.org/10.1007/S11277-022-10075-8/TABLES/9
132. Yadav, P., Sharma, S.C., & Rishiwal, V. (2022). Hybrid localization scheme using K-fold optimization with machine learning in WSN. *International Journal of Communication Systems*, *35(12)*. https://doi.org/10.1002/dac.5206.
133. Chen, J., Sackey, S. H., Anajemba, J. H., Zhang, X., & He, Y. (2021). Energy-efficient clustering and localization technique using genetic algorithm in wireless sensor networks. *Complexity, 2021*, 1–12. https://doi.org/10.1155/2021/5541449
134. Shen, Z., Zhang, T., Tagami, A., & Jin, J. (2021). When RSSI encounters deep learning: An area localization scheme for pervasive sensing systems. *Journal of Network and Computer Applications., 173*, 102852. https://doi.org/10.1016/J.JNCA.2020.102852
135. Guo, R., Qin, D., Zhao, M., & Xu, G. (2020). Mobile target localization based on iterative tracing for underwater wireless sensor networks. *International Journal of Distributed Sensor Networks*, *16(7)*. https://doi.org/10.1177/1550147720940634.
136. Singh, A., Kotiyal, V., Sharma, S., Nagar, J., & Lee, C. C. (2020). A machine learning approach to predict the average localization error with applications to wireless sensor networks. *IEEE Access, 8*, 208253–208263. https://doi.org/10.1109/ACCESS.2020.3038645
137. Ren, Q., Zhang, Y., Nikolaidis, I., Li, J., & Pan, Y. (2020). RSSI quantization and genetic algorithm based localization in wireless sensor networks. *Ad Hoc Networks, 107*, 102255. https://doi.org/10.1016/J.ADHOC.2020.102255
138. Cai, X., Wang, P., Cui, Z., Zhang, W., & Chen, J. (2020). Weight convergence analysis of DV-hop localization algorithm with GA. *Soft Computing, 24*(23), 18249–18258. https://doi.org/10.1007/S00500-020-05088-Z
139. Anusha, K. S., Ramanathan, R., & Jayakumar, M. (2020). Link distance-support vector regression (LD-SVR) based device free localization technique in indoor environment. *Engineering Science and Technology, an International Journal, 23*(3), 483–493. https://doi.org/10.1016/J.JESTCH.2019.09.004
140. Rauchenstein, L.T., Vishnu, A., Li, X., & Deng, Z.D. (2018). Improving underwater localization accuracy with machine learning. *Review of Scientific Instruments*, *89(7)*. https://doi.org/10.1063/1.5012687.
141. Wen, W., Wen, X., Yuan, L., & Xu, H. (2018). Range-free localization using expected hop progress in anisotropic wireless sensor networks. *EURASIP Journal on Wireless Communications and Networking, 2018*(1), 1–13. https://doi.org/10.1186/S13638-018-1326-8/FIGURES/11
142. Sun, Y., Zhang, X., Wang, X., & Zhang, X. (2018). Device-free wireless localization using artificial neural networks in wireless sensor networks. *Wireless Communications and Mobile Computing, 2018*, 1–8. https://doi.org/10.1155/2018/4201367
143. Fang, X., Jiang, Z., Nan, L., & Chen, L. (2018). Optimal weighted K-nearest neighbour algorithm for wireless sensor network fingerprint localisation in noisy environment. *IET Communications, 12*(10), 1171–1177. https://doi.org/10.1049/IET-COM.2017.0515
144. Phoemphon, S., So-In, C., & Tao Niyato, D. (2018). A hybrid model using fuzzy logic and an extreme learning machine with vector particle swarm optimization for wireless sensor network localization. *Applied Soft Computing, 65*, 101–120. https://doi.org/10.1016/J.ASOC.2018.01.004
145. Wang, Z., Zhang, H., Lu, T., Sun, Y., & Liu, X. (2017). A new range-free localisation in wireless sensor networks using support vector machine. *International Journal of Electronics, 105*(2), 244–261. https://doi.org/10.1080/00207217.2017.1357198
146. Sharma, G., & Kumar, A. (2018). Modified energy-efficient range-free localization using teaching–learning-based optimization for wireless sensor networks. *IETE Journal of Research, 64*(1), 124–138. https://doi.org/10.1080/03772063.2017.1333467
147. Banihashemian, S. S., Adibnia, F., & Sarram, M. A. (2018). A new range-free and storage-efficient localization algorithm using neural networks in wireless sensor networks. *Wireless Personal Communications, 98*(1), 1547–1568. https://doi.org/10.1007/S11277-017-4934-4/FIGURES/11

148. Kang, J., Park, Y. J., Lee, J., Wang, S. H., & Eom, D. S. (2018). Novel leakage detection by ensemble CNN-SVM and graph-based localization in water distribution systems. *IEEE Transactions on Industrial Electronics, 65*(5), 4279–4289. https://doi.org/10.1109/TIE.2017.2764861
149. Sun, B., Guo, Y., Li, N., & Fang, D. (2017). Multiple target counting and localization using variational bayesian EM algorithm in wireless sensor networks. *IEEE Transactions on Communications, 65*(7), 2985–2998. https://doi.org/10.1109/TCOMM.2017.2695198
150. Z. Wang, H. Liu, S. Xu, X. Bu, and J. An, "Bayesian Device-Free Localization and Tracking in a Binary RF Sensor Network," *Sensors 2017, Vol. 17, Page 969*, vol. 17, no. 5, p. 969, Apr. 2017, doi: https://doi.org/10.3390/S17050969.
151. Li, X., Ding, S., & Li, Y. (2017). Outlier suppression via non-convex robust PCA for efficient localization in wireless sensor networks. *IEEE Sensors Journal, 17*(21), 7053–7063. https://doi.org/10.1109/JSEN.2017.2754502
152. Correa, A., Llado, M. B., Morell, A., & Vicario, J. L. (2016). Indoor pedestrian tracking by on-body multiple receivers. *IEEE Sensors Journal, 16*(8), 2545–2553. https://doi.org/10.1109/JSEN.2016.2518872
153. Janapati, R., Balaswamy, C., Soundararajan, K., & Venkanna, U. (2016). Indoor localization of cooperative WSN using PSO assisted AKF with optimum references. *Procedia Computer Science, 92*, 282–291. https://doi.org/10.1016/J.PROCS.2016.07.357
154. El Assaf, A., Zaidi, S., Affes, S., & Kandil, N. (2016). Robust ANNs-based WSN localization in the presence of anisotropic signal attenuation. *IEEE Wireless Communications Letters, 5*(5), 504–507. https://doi.org/10.1109/LWC.2016.2595576
155. Zhu, F., & Wei, J. (2017). Localization algorithm for large scale wireless sensor networks based on fast-SVM. *Wireless Personal Communications, 95*(3), 1859–1875. https://doi.org/10.1007/S11277-016-3665-2
156. Gharghan, S. K., Nordin, R., Ismail, M., & Ali, J. A. (2016). Accurate wireless sensor localization technique based on hybrid PSO-ANN algorithm for indoor and outdoor track cycling. *IEEE Sensors Journal, 16*(2), 529–541. https://doi.org/10.1109/JSEN.2015.2483745
157. So-In, C., Permpol, S., & Rujirakul, K. (2016). Soft computing-based localizations in wireless sensor networks. *Pervasive and Mobile Computing, 29*, 17–37. https://doi.org/10.1016/J.PMCJ.2015.06.010
158. Bernas, M., & Płaczek, B. (2015). Fully connected neural networks ensemble with signal strength clustering for indoor localization in wireless sensor networks, vol. *2015*. https://doi.org/10.1155/2015/403242.
159. Payal, A., Rai, C.S., & Reddy, B.V.R. (2014). Artificial neural networks for developing localization framework in wireless sensor networks. In *2014 International Conference on Data Mining and Intelligent Computing, ICDMIC 2014*. https://doi.org/10.1109/ICDMIC.2014.6954228.



Ms. Preeti Yadav is working as an Assistant Professor in the Department of Computer Science and Information Technology, Faculty of Engineering and Technology, MJP Rohilkhand University, Bareilly, Uttar Pradesh, India. She has 15 years of experience in academics. She obtained B. Tech degree in Computer Science and Engineering in the year 2007 from Uttar Pradesh Technical University, Lucknow (SRMSCET), India, and received her M. Tech degree in Computer Science and Engineering from Integral University, Lucknow, India, in the year 2014. She is pursuing Ph.D. from Indian Institute of Technology Roorkee, Roorkee, India. She has 7 patents in her credit out of which 5 are national and 2 are international. She has worked on project sponsored by MHRD/TEQIP. She is a member of IEEE. She has worked as Convener Student Activities Committee, IEEE Uttar Pradesh Section. She has been reviewer of many journals/conferences. She has published more than 25 research papers in various journals and conferences of international repute. Her current research interest includes Wireless Sensor Networks, IoT and Machine Learning.

Professor S. C. Sharma (https://www.iitr.ac.in/~DPT/scs60fpt) received M.Sc. (Electronics, IITR), M. Tech. (Electronics & Communication Engg., IITR) and Ph.D. (Electronics & Computer Engg., IITR) in 1981, 1983, and 1992 respectively from IIT Roorkee (erstwhile University of Roorkee). He started his career as an R & D Engineer in 1983 then joined the teaching profession in Jan. 1984 at IIT-Roorkee and continuing till date. He has more than 35 years of teaching and research experience at IIT Roorkee. He has published over three hundred research papers in national and international journals (152)/conferences (150) and supervised more than 30 projects/dissertations of PG students. He has supervised 20 Ph.D. in the area of Computer Networking, Wireless Network, Computer Communication, Cloud & its security, mobile computing and continuing supervising Ph.D. in the same area. He has successfully completed several major research projects funded by various Govt. Agencies like AICTE, CSIR, UGC, MHRD, DST, DRDO, and many minor research projects related to Communication and SAW filter design sponsored by the Government of India. IIT-Roorkee has awarded him the Khosla annual research prize with the best research paper. His many research papers have been awarded by National and International Committees and Journals. He has worked as a research scientist at FMH, Munchen, Germany, and visited many countries (UK, France, Germany, Italy, Switzerland, Canada, UAE, Thailand, Netherlands, etc.) related to research work. He has chaired sessions of International Conferences and delivered invited talks at various forums. He is the active reviewer of the IEEE Journals and Editor of various reputed International and National Journals. He is the honorary member of NSBE, ISOC, and IAENG, USA. He has also worked as group leader of Electronics & Instrumentation Engg. Department of BITS-Pilani-Dubai Campus, from Aug. 2003 to Aug. 2005. Presently he is continuing as Professor at IIT Roorkee, Roorkee, India.