UTM UNIVERSITI TEKNOLOGI MALAYSIA
INTERNATIONAL JOURNAL OF INNOVATIVE COMPUTING
ISSN 2180-4370
Journal Homepage : https://ijic.utm.my/

Metaheuristic Optimization Techniques for Localization in Outdoor Wireless Sensor Networks: A Comprehensive Review

Bassam Gumaida[1]* & Adamu Abubakar Ibrahim[2]
Department of Computer Science,
International Islamic University Malaysia,
50728 Kuala Lumpur, Malaysia
Email: gumaida_phd@hotmail.com[1]; adamu@iium.edu.my[2]

Submitted: 13/5/2024. Revised edition: 1/3/2025. Accepted: 21/3/2025. Published online: 27/5/2025
DOI: https://doi.org/10.11113/ijic.v15n1.454

***Abstract*—During the last two decades, Wireless Sensor Networks (WSNs) have attracted significant attention from researchers and sensor manufacturing companies alike. WSNs find applications in various environmental monitoring tasks such as weather monitoring, temperature observation, humidity measurement, and military surveillance. These networks typically consist of hundreds to thousands of sensor nodes deployed across the target area. Each sensor node is responsible for collecting specific data and transmitting it to the processing center. However, several constraints, including power consumption, energy-saving measures, and deployment costs, limit the functionality of sensor nodes. Additionally, the accuracy of transmitted data is influenced by the surrounding environment. This paper provides an overview of localization algorithms, including centralized and distributed algorithms. It also delves into distance measurement techniques such as Time of Arrival (ToA), Time Difference of Arrival (TDoA), Angle of Arrival (AoA), and Received Signal Strength Indicator (RSSI). Methodologies of localization, such as range-based and range-free approaches, are discussed, along with various range-based localization techniques like Sum-Dist-Min-Max, Bounding box, geometric methods, and general techniques. The paper also examines influencing factors such as noise, path loss, propagation model, connectivity, and device limitations and their impact on localization measurements. The primary objective of this paper is to review localization algorithms based on metaheuristic optimization techniques to improve localization accuracy. This paper serves as a comprehensive background on localization algorithms and methods used in wireless sensor networks, offering insights for researchers to develop efficient localization algorithms tailored to specific application requirements in diverse work environments.**

***Keywords*—Wireless Sensor Networks, Ranging Model, RSSI, Optimization Techniques, Localization Techniques, Measurement influencing factors**

I. INTRODUCTION

The development of Wireless Sensor Networks (WSNs) has seen rapid growth over the past two decades, driven by advancements in wireless communication and sensing devices. WSNs, comprising distributed nodes numbering from hundreds to thousands, find applications in various environments such as environment monitoring, wildlife tracking, healthcare, military surveillance, and infrastructure maintenance in factories [1], [2], [3]. Despite their wide-ranging applications, WSNs face several limitations including node battery depletion, hardware issues, node detection, node position estimation, network expansion, and deployment costs. One significant challenge is the coverage capacity of sensor nodes.

Localization, or determining the location information of sensed data, is crucial for many WSN applications to make the collected data meaningful. Localization algorithms play a vital role in applications such as monitoring, tracking, and geographic routing, which require accurate node coordinates. These algorithms aim to assign geographic coordinates to all sensed data collected from sensor nodes within the WSN area to effectively manage and respond to them [4], [5].

The growing reliance on devices and sensed data necessitates more efficient and accurate localization methods. Traditional localization techniques face challenges in accurately and cost-effectively localizing all devices and Sensor Nodes (SNs), particularly in large deployment areas common in Internet of Things (IoT) applications. To address these challenges, optimization techniques and mobile anchors have been proposed to estimate device positions more effectively.

During the last ten years, a significant number of localization algorithms have been developed for use in Wireless Sensor Networks (WSNs). These algorithms employ various ranging techniques to determine the distances between sensor nodes and anchors. Examples of these techniques include Angle-of-Arrival (AOA), Time-Difference-of-Arrival (TDOA), and Received Signal Strength Indicator (RSSI). Among these techniques, RSSI is particularly popular because it is readily available in WSN devices and does not require additional equipment or cost. However, the RSSI-based ranging method suffers from low precision due to environmental noise and other factors.

Over the past two decades, numerous algorithms have been proposed for WSN localization, all sharing the common approach of utilizing beacon nodes or anchor nodes to determine the positions of unknown nodes. These anchor nodes determine their positions either through GPS or manual pre-programming during installation [5]. Nodes that are distributed throughout the environment and cannot determine their positions are referred to as unknown nodes. Given the limitations of GPS in non-line-of-sight environments and its high hardware cost, it may not be suitable for localizing unknown nodes [6]. Therefore, there is a need to develop new algorithms for localization.

This paper aims to achieve the following goals:

- Provide an overview of the sensor device and its components.
- Discuss localization algorithms, including centralized and distributed approaches.
- Explain distance measurement techniques such as Time of Arrival (ToA), Time Difference of Arrival (TDoA), Angle of Arrival (AoA), and Received Signal Strength Indicator (RSSI).
- Examine localization methodologies, including ranged-based and range-free methods.
- Investigate various influencing factors affecting localization measurements, such as noise, path loss, propagation models, connectivity issues, and device limitations, and their impact on localization accuracy.
- Review localization algorithms based on optimization techniques to improve localization accuracy.

The subsequent sections of this paper are structured as follow: Section 2 introduces an overview of the sensor devices and their components, while Section 3 presents distance measurement techniques. Methodologies of localization are addressed in Section 4, followed by a description of localization influencing factors in Section 5. Section 6 covers the WSN network model and propagation model. In Section 7, a review of localization algorithms based on optimization techniques is provided. Finally, Section 8 concludes the paper with recommendations for future research.

II. AN OVERVIEW OF THE SENSOR DEVICE

A sensor device is a crucial component in various industries and applications, designed to detect and measure specific physical properties or environmental phenomena. These devices play a pivotal role in collecting data for monitoring, control, and automation systems. The main components of a typical sensor device include a sensing unit, processing unit, transceiver unit, power unit, and location finding system, [7], [8] as shown in Fig. 1.

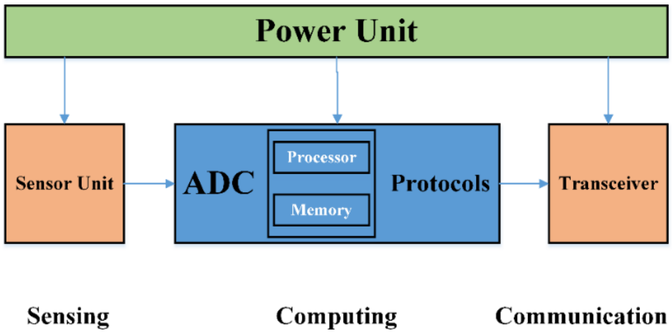

Fig. 1. Sensor device components

Following is a brief introduction to the typical components of a sensor device:

- Sensor unit: This is the core component of the sensor that directly interacts with the physical parameter it’s designed to measure. It undergoes changes in response to variations in the measured property, like temperature, pressure, humidity, light, or motion.
- Analog to digital converter (ADC): In many cases, the sensing element needs to convert its physical response into an electrical signal that can be processed and analyzed. The transducer performs this conversion, changing physical variations into voltage, current, or digital signals.
- Processing unit: To ensure the accuracy and reliability of the measured data, sensor devices often include processing unit. This unit may amplify, filter, or otherwise modify the raw signal to improve its quality and compatibility with downstream electronics. This unit always comprise processor and memory.
- Transceiver: This is the communication unit; where sensor devices typically have an output interface that connects to external systems or devices, allowing the processed data to be transmitted or displayed for further analysis or action. This can be in the form of analog voltage, current, or digital signals.
- Power Supply: Sensors require a power source to operate. The power supply can be as simple as a battery for portable devices or a more complex power management system for larger sensor networks.

The components of sensor devices collaborate to detect, measure, and transmit data concerning the physical environment, supporting diverse applications like environmental monitoring, industrial automation, healthcare, and consumer electronics. This synergy enhances the appeal and cost-effectiveness of monitoring and tracking applications, especially in expansive deployment areas, as demonstrated by the benefits of utilizing Wireless Sensor Networks (WSNs) [9]. This advancement paves the way for a future where data from millions or even billions of sensor devices can be gathered, processed, and leveraged collaboratively within a global Internet of Things (IoT) framework [10]. The IoT heralds a trans-formative era in internet technology, facilitating seamless communication among a vast array of users and devices by linking various communication elements through a unified networking approach utilizing the internet [11].

The success of the Internet of Things (IoT) hinges significantly on wireless communication and the ability to accurately determine the location of connected devices. This new generation of technology faces several key challenges, including managing energy consumption, storage, device diversity, precision localization, and communication bandwidth. Additionally, a diverse array of applications within this generation requires the ability to locate and interact with connected devices effectively. These applications span geographic routing, marketing initiatives, data aggregation algorithms, and environmental monitoring efforts [12].

Upon observing the multitude of entities involved, coupled with their diverse models and locations, it has become imperative to delve into existing localization systems and discern their capacity to address both scalability and mobility. Furthermore, understanding how these systems can fulfill the requirements of prompt and precise localization operations is crucial [13]. An integral aspect of the IoT in its latest iteration is the accurate determination of sensor node positions [11], [14]. In numerous WSNs applications, the data gathered or monitored loses its significance without accompanying location information. Essentially, processing units cannot effectively handle or respond to data collected by sensor nodes lacking location data. Therefore, determining the event's location is imperative for taking appropriate action. While one common solution involves equipping every sensor node with a Global Positioning System (GPS) function to obtain their locations, this approach is considered sub-optimal due to its costly hardware and limited accuracy in environments lacking line of sight.

Alternatively, a substantial number of localization algorithms have been proposed, all operating on the fundamental principle of estimating the positions of unlocalized sensor nodes based on prior knowledge of the absolute positions of certain nodes, referred to as beacons or anchors. This process is typically achieved through distance and ranging measurements such as signal strength, time of arrival, or network information.

Hence, it is crucial to devise new localization techniques for estimating the positions of unlocalized sensor nodes without relying on GPS. As mentioned, Wireless Sensor Network (WSN) localization algorithms determine the coordinates of unlocalized sensor nodes with the assistance of anchor nodes. These anchor nodes can either be dedicated to sensor nodes, such as base stations, or realized through sensor nodes with enhanced capabilities compared to others in the network, including the ability to determine their absolute location. Anchor nodes are aware of their positions, either through GPS services or manual configuration during deployment [12]. In the localization process, anchor nodes initially broadcast their coordinates along with operational instructions to unlocalized sensor nodes. Subsequently, unlocalized sensor nodes utilize the received positions of anchor nodes to estimate their own positions.

III. DISTANCE MEASUREMENT AND LOCALIZATION TECHNIQUES

In most localization algorithms, the localization process typically involves two stages. Firstly, the distance or angle between unlocalized sensor nodes and anchors is estimated using various measurement techniques. Secondly, the obtained distance or angle information is utilized in localization algorithms to estimate the positions of unlocalized sensor nodes. These localization estimation techniques can generally be categorized into two methods: centralized and distributed. In the centralized method, the localization process is centralized within a processing center, where distance or angle information collected from the unlocalized sensor nodes is processed to determine their positions. On the other hand, in a distributed system, each unlocalized sensor node independently estimates its own position. While distributed localization techniques offer scalability advantages, they do require unlocalized sensor nodes to possess sufficient processing power to perform self-localization.

A. Distance Measurement Techniques

This section provides a comprehensive overview of the various measurement techniques utilized by localization algorithms to estimate the distance between sensor nodes and anchors in WSNs. These techniques can be broadly categorized into four main groups: RSSI-based, angle-based, time-based, and phase-based, as illustrated in Fig. 2.

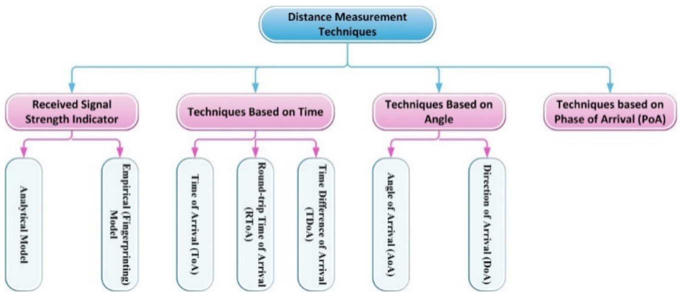

Fig. 2. Distance measurement techniques

1) Techniques based on Received Signal Strength Indicator (RSSI)

RSSI, or Received Signal Strength Indicator, refers to the power level of the signal received by the receiver of WSN nodes. It is important to note that the lower the value of RSSI, the greater the attenuation of the signal, which occurs due to energy loss during transmission through the air. As a result, distance measurement techniques utilizing RSSI are based on the principle that signal strength exhibits an inverse relationship with the distance between the transmitter and the receiver [15], [16], [17], [18], [19], [20]. Therefore, a thorough understanding and in-depth study of signal attenuation characteristics are essential for establishing the relationship between RSSI and actual distance. RSSI models are typically classified into Analytical and Empirical models. Analytical models relate RSSI to actual distance based on path-loss propagation models, which model the electromagnetic wave behavior. In such models, the attenuation ratio of the signal over distance is assumed to be known in advance. According to the free space theory, RSSI exhibits an inverse relationship with the square of the distance (*d*) between the transmitter and the receiver. Based on [21], this relationship is formulated using the Friis equation as follows:

$$\boldsymbol{P_r(d) = \frac{P_t\, G_t\, G_r \lambda^2}{(4\pi)^2 d^2}} \qquad (1)$$

Where:

- P_t is the transmitted power.
- G_t and G_r are the transmitter and receiver antenna gain respectively.
- λ is the wavelength of the transmitted signal in meters.

A widely employed model that utilizes the RSSI function is the Lognormal-shadowing model (LNSM), favored for its simplicity and the effective correlation between signal attenuation and distance. The following formula depicts the relationship of the RSSI function in the LNSM:

$$\boldsymbol{RSSI_d(dBm) = RSSI_{d_0}(dBm) - 10n\log\frac{d}{d_0} + X_\sigma} \qquad (2)$$

Where:

- $RSSI_d$ illustrates the power of the signal received by an unknown node (non-anchor node) from the sender.
- $RSSI_{d0}$ is the power of the received signal by an unknown node at reference distance d_0 , usually this distance is 1m from an anchor node, and often the factory of WSN devices shows the $RSSI_{d0}$ value for their products, for example (-45 dBm) in some devices [22].
- d denotes the distance between an unknown node and an anchor node.
- (10n log d/d_0) stands for the Pathloss exponent, generally, its value is in the range of 2 to 6.5 depending on the propagation media or environment (see TABLE I).
- Xσ represents the shadowing factor or the random variation in RSS, where It can be defined as a Gaussian distributed random variable (in dB) with zero mean and σ standard deviation (in dB).

TABLE I. PATH LOSS EXPONENT RANG

Environment	N
Urban macro cells	3.7 - 6.5
Urban micro cells	2.7 - 3.5
Office building (same floor)	1.6 - 3.5
Office building (multiple floors)	2 - 6
Store	1.8 - 2.2
Factory	1.6 - 3.3
Home	3

One drawback of this technique is that as the distance increases, the signal weakens, resulting in a decrease in the wireless data rate. This can lead to reduced data throughput and errors in distance measurement.

2) *Techniques Based on Time*

These techniques rely on calculating the propagation time taken by the signal to travel between the transmitter and receiver. The transmitted signal may be acoustic, electromagnetic, or ultrasound. Time-based techniques are typically classified into three main categories:

- Time of Arrival (ToA).
- Round-trip Time of Arrival (RToA).
- Time Difference of Arrival (TDoA).

In the first category, denoted as ToA (Time of Arrival), as illustrated in Fig. 3, the distance between the transmitter and receiver is determined using the following equation:

$$\boldsymbol{d = C_r \times (t_1 - t_0)} \qquad (3)$$

Where:

- C_r refers to the signal speed.
- t_0 and t_1 represent the moments of transmission and reception respectively as shown in Figure 3.

In the second category, designated as RToA (Round-trip Time of Arrival), as depicted in Fig. 4, the measurement of the distance between the transmitter and receiver is achieved by applying the following formula:

$$\boldsymbol{d = C_r \times \frac{(t_1 - t_0)}{2}} \qquad (4)$$

Where:

- C_r refers to the signal speed.
- (t_1 - t_0) represents the round-trip time of flight as shown in Fig. 4.

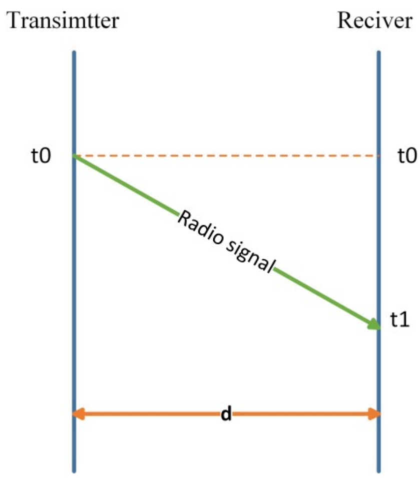

Fig. 3. Time of arrival technique

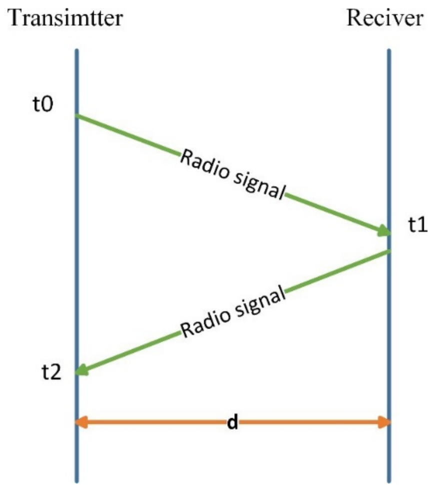

Fig. 4. Round-trip time of arrival technique

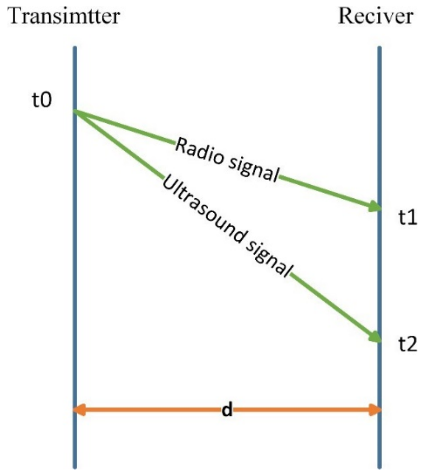

Fig. 5. Time difference of arrival technique

In the third category, designated as TDoA (Time Difference of Arrival), as depicted in Fig. 5, the measurement of the distance between the transmitter and receiver is achieved by applying the following formula:

$$\boldsymbol{d} = \frac{\boldsymbol{C_r} \times \boldsymbol{C_u} \times (\boldsymbol{t_1} - \boldsymbol{t_0})}{\boldsymbol{C_r} - \boldsymbol{C_u}} \qquad (5)$$

Where:

- C_r and C_u are respectively the propagation speed of the RF and ultrasound signals.
- t_1 and t_2 are the arrival times at the receiver side for both signals respectively as shown in Fig. 5.

A limitation of this technique arises from the necessity to synchronize the nodes using synchronous clocks. When the synchronization of these clocks is inaccurate, it directly translates to imprecise positions, compromising the overall effectiveness of the method.

3) Techniques based on Angle

These techniques are categorized based on the method used to calculate the angle, with some techniques computing the Angle of Arrival (AoA) and others determining the Direction of Arrival (DoA). The measurement in these techniques relies on calculating the angle between the sensor (unlocalized) node and the anchor node relative to a reference direction. This angle, also known as orientation [23], is determined based on whether the reference direction is absolute or relative. In absolute orientation, the reference direction is fixed, typically aligned with the North direction, as depicted in Fig. 6. Conversely, in relative orientation, the reference direction is known relative to the North direction [17], allowing each unlocalized sensor node to have its own orientation axis, as illustrated in Fig. 7.

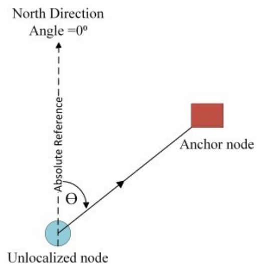

Fig. 6. Absolute orientation

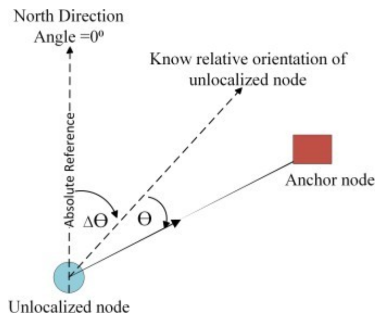

Fig. 7. Relative orientation

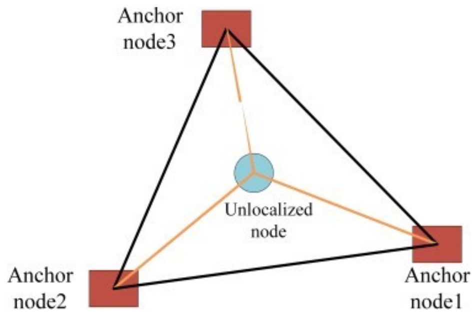

Fig. 8. Unknown orientation

In another scenario where the reference direction is unknown, trilateration is employed using three anchor nodes to determine the location of the unlocalized sensor nodes. In this case, the angle of the third anchor is used to establish the reference direction, as depicted in Fig. 8. However, this technique is subject to limitations in terms of accuracy, which can be affected by environmental factors such as shadowing and multi-tracking.

4) Techniques based on Phase of Arrival (PoA)

These techniques rely on the received signal phase to estimate the distance between sensor nodes. Phase of Arrival (PoA) is based on calculating the phase difference of the received signal between the transmitter antenna and receiver antenna [24], [25]. However, one disadvantage of PoA is the requirement of Line of Sight (LoS) between the transmitter antenna and receiver antenna. Additionally, it needs to be combined with Received Signal Strength Indicator (RSSI) and Time of Arrival (ToA) to increase accuracy.

B. Localization Techniques

A considerable deal of localization algorithms can be classified into different categories, for example:

- Localization algorithms based or not based on anchors.
- Position calculation is distributed or centralized [26].

In the anchor-based category, anchor nodes possess prior knowledge of their own positions, either acquired through GPS systems or manually during setup. These positions are then used to estimate the positions of unknown nodes through trilateration. In contrast, the anchor-free category relies on connectivity information between unknown nodes and anchor nodes to determine the positions of unknown nodes, resulting in relative positions. Therefore, the anchor-based category typically achieves higher localization accuracy compared to the anchor-free category. Within the distributed category, unknown nodes compute their own positions, leading to potential rapid energy consumption. Conversely, in the centralized category, all information is processed in a central processing center, conserving the energy of sensor nodes. As a result, the centralized category is more power-efficient than the distributed category [27].

However, achieving high localization accuracy requires addressing sensitive and critical factors such as the number of required anchors and power consumption. While algorithms with a larger number of anchors tend to achieve higher localization accuracy, this also increases the cost and power consumption of WSNs. Recently, there has been a shift towards using optimization techniques to enhance position estimation accuracy instead of traditional techniques like trilateration and angulation. These optimization techniques primarily aim to enhance the measurement of the Received Signal Strength Indicator (RSSI) technique. They encompass Particle Swarm Optimization (PSO) and its variants [26], Differential Evolution (DE), Pattern Search (PS), Ant Colony Optimization (ACO) [28], Genetic Algorithm (GA) [29], and Local Unimodal Sampling (LUS).

IV. METHODOLOGIES OF LOCALIZATION

Localization measurement techniques are classified into two categories relied on the number of hops.

- One-hop.
- Multi-hop.

This paper exclusively examines the one-hop technique, where an unlocalized sensor node can achieve localization if it has sufficient one-hop connectivity to neighboring anchors. The primary localization techniques based on the one-hop model include Multilateration, Bounding Box, and Angulation. Multilateration and Angulation utilize Linear Least Squares for their calculations. Multilateration and Bounding Box estimate the position of the unlocalized sensor node based on distance measurements, while Angulation relies on Angle of Arrival (AoA) for position estimation.

A. Multilateration

Multilateration is a conventional localization technique that utilizes distance measurements, typically obtained through techniques like RSSI or ToA, to estimate the positions of unlocalized sensor nodes.

B. Bounding Box

Another computationally efficient localization technique, known as the Bounding Box or min-max algorithm, offers an alternative to Multilateration. In this method, rectangles are used instead of circles to estimate the positions of sensor nodes, as depicted in Fig. 9. Each anchor node is surrounded by a rectangle, the dimensions of which are determined by the anchor node's location and the estimated distance to the sensor node. The estimated location of the unlocalized sensor node is then determined by finding the center of the intersection of all rectangles. The Bounding Box method is noted for its ability to provide accurate solutions close to those obtained through Multilateration while requiring lower computational resources.

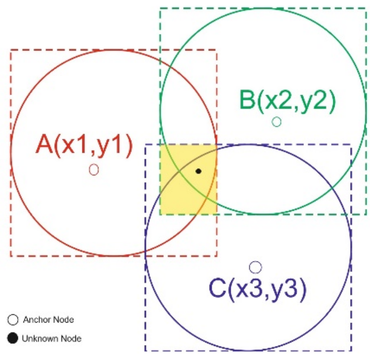

Fig. 9. Bounding box technique

C. Localization using Angulation

Another method for estimating the location of sensor nodes is Angulation, which utilizes angle information and properties of triangles to calculate the positions of unlocalized sensor nodes, as illustrated in Fig. 10. As discussed previously in the section on angle-based techniques, sensor nodes can be localized in a 2D space using two anchor nodes, employing triangulation. However, in a 3D space, triangulation requires additional information which is the height of the location of anchor nodes.

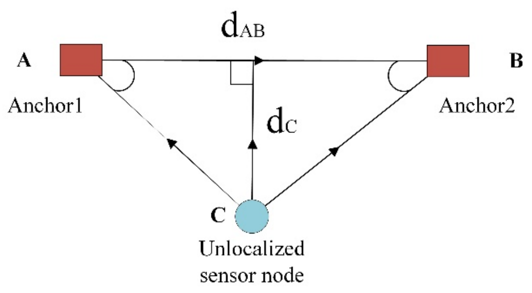

Fig. 10. Angulation method scenario

D. Localization using Sum-Dist-Min-Max Method

The SumDistMinMax method operates by first allowing anchor devices to broadcast their respective positions. When a sensor device (an unknown node) (X) detects the position of an anchor node (Y), it estimates the distance between them using the Sum-Dist approach. Sum-Dist approach serves as a fundamental technique for determining distances to anchor nodes. Each anchor node in the Wireless Sensor Network (WSN) transmits a message containing its ID, coordinates, and an initialized path length of zero. Upon receiving this message, the sensor device (an unknown node) calculates the distance from the sender, adds it to the path length, and then rebroadcasts the updated message [30].

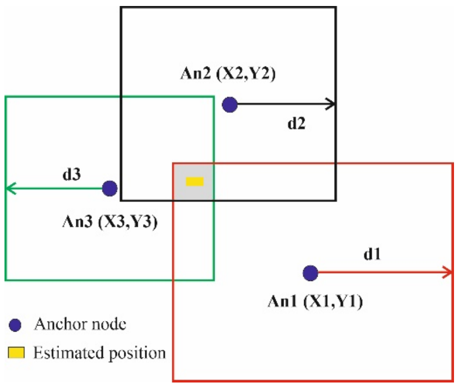

Fig. 11: Mix max method

Through this process, each sensor node in the network derives an estimated distance to multiple anchors. However, only the shortest distance is considered for position estimation. The Sum-Dist approach is advantageous due to its speed and minimal computational requirements. Despite these benefits, a major limitation is the accumulation of range errors when distance information propagates across multiple hops. To refine the position estimation, the final step employs the MinMax method. This technique attempts to establish a bounding box that encompasses the unknown sensor node. The estimated position of the node is then determined by calculating the center of gravity of this box. This process effectively enhances the localization accuracy, as depicted in Fig. 11

E. Localization Using Mobile Anchor

The localization techniques discussed earlier primarily rely on static anchor nodes. However, there is a growing trend towards utilizing mobile anchors instead of static ones. This trend aims to reduce the required number of anchor nodes in the target area and address the limitations associated with the transmission range of static anchors [31]. Mobile anchors move through the target area, scanning it and collecting signals from unlocalized sensor nodes to estimate their locations. Localization based on mobile anchors offers a cost-effective solution for WSN applications, as a single mobile anchor can serve the purpose of multiple static anchors in the same target area [13], [32], [33], [34].

F. Localization Using Optimization Techniques

Contemporary trends in localization methodologies within Wireless Sensor Networks (WSNs) have shifted towards the adoption of optimization techniques, departing from conventional estimation approaches. These optimization methodologies show promise in enhancing localization precision, especially in measurements reliant on Received Signal Strength Indication (RSSI). Various optimization methods have been employed in WSN localization, including black box optimization techniques such as Pattern Search (PS), Differential Evolution (DE), Particle Swarm Optimization (PSO) and its variants [35], Genetic Algorithm (GA) [36], Local Unimodal Sampling (LUS), Intelligent Water Drops (IWD) algorithm [37], and Ant Colony Optimization (ACO) [38].

Additionally, hybrid techniques have emerged, combining advantageous features from different optimization methods, such as the hybrid of Particle Swarm Optimization with Variable Neighborhood Search (HPSOVNS) [39], graph embedding with polynomial mapping (GEPM), Improved Self-Adaptive Inertia Weight Particle Swarm Optimization (ISAPSO), and many others.

The main aim of this paper is to provide an extensive examination of localization algorithms that utilize optimization techniques to enhance localization accuracy. This review will explore the different optimization based strategies employed in localization, evaluating their effectiveness and impact on improving localization precision. Furthermore, we will investigate the essential factors, methodologies, and recent developments in localization algorithms, particularly focusing on optimization approaches. By doing so, this review seeks to contribute to a better understanding of how optimization contributes to the refinement of localization methods and its significance across various applications and industries. The following Table II outlines the advantages and disadvantages of the aforementioned localization methods.

TABLE II. ADVANTAGES AND DISADVANTAGES OF LOCALIZATION METHODS

Method	Advantages	Disadvantages
Multilateration	1: Provides acceptable localization accuracy when distances are measured accurately. -2: Performs well with a high density of anchors.	1: Requires high precision in distance measurements. 2: Affected by noise and signal attenuation. 3: Performance declines in NLOS conditions.
Bounding Box	1: Simple method with efficient computation. 2: Does not require complex calculations.	1: Less accurate compared to other methods. 2: Performance depends on the status and placement of anchors.
Angulation	1: High accuracy when angle measurements are precise. 2: Requires fewer anchor nodes compared to multilateration.	1: Sensitive to measurement errors. 2: Requires special hardware for implementation.
SumDistMinMax	1: Fast and computationally efficient method. 2: Requires minimal resources.	1: Accumulated errors from multi-hop distance propagation. 2: Accuracy is affected by node density and WSN topology.
Mobile Anchor	1: Increases accuracy with a minimal number of anchors, starting from one mobile anchor. 2: Can be used in inaccessible environments.	1: Implementation requires more time due to anchor movement. 2: Higher energy consumption for moving anchors.
Optimization Techniques	1: Achieves high localization accuracy even in noisy WSNs. 2: Can mitigate errors from traditional methods.	1: Implementation is complex and requires a powerful processing unit. 2: Efficiency depends on the optimization algorithm used.

V. LOCALIZATION INFLUENCING FACTORS

As stated previously, localization in wireless sensor networks (WSNs) refers to the method of estimating the actual locations of sensor nodes in the network. Accurate localization is essential for the majority of WSN applications, such as environmental monitoring, target tracking, and asset management. There are several factors that can influence the accuracy and reliability of localization in WSNs as follows:

1. Sensor Node Capabilities:
- Hardware Sensors: The type and quality of sensors (e.g., GPS, accelerometer, ranging sensors) used by sensor nodes play a significant role in localization accuracy.
2. Localization Techniques:
- Range-Based vs. Range-Free: The choice between range-based (e.g., distance measurements) and range free (e.g., connectivity-based) localization techniques can impact accuracy and complexity.
- Multilateration: Techniques based on measuring distances between nodes can be affected by the precision of distance measurements.
3. Anchor Nodes:
- Anchor Placement: The deployment and placement of anchor nodes with known locations in the network can significantly improve localization accuracy.
4. Communication Environment:
- Signal Propagation: Signal propagation conditions, including obstacles, multipath fading, and interference, can affect the accuracy of distance measurements and ranging-based techniques.
- Communication Range: The maximum communication range between nodes can impact the network's ability to determine neighbor nodes.
5. Network Density:
- Node Density: Higher node density can lead to better localization accuracy as there are more reference points for ranging and triangulation.
6. Localization Algorithms:
- Algorithm Selection: The choice of localization algorithm, such as trilateration, fingerprinting, or probabilistic methods, can influence accuracy.
- Error Models: The accuracy of error models used by localization algorithms affects their performance.
7. Clock Synchronization:
- Time Synchronization: Synchronized clocks among sensor nodes are critical for time-of-flight-based distance measurements.
8. Environmental Conditions:
- Temperature and Humidity: Environmental factors can affect signal propagation and sensor node behavior.
9. Node Mobility:
- Mobile Nodes: In scenarios with mobile sensor nodes, continuous updates of node positions are required.
10. Wireless Communication Range Estimation:
- Received Signal Strength Indicator (RSSI): Estimations of signal strength can be used for localization, but they are susceptible to interference and signal variations.
11. Power Constraints:
- Energy Efficiency: Localization methods must consider the energy constraints of sensor nodes and minimize power consumption during localization operations.
12. Localization Infrastructure:
- Localization Beacons: The presence and positioning of dedicated localization beacons or reference nodes can improve accuracy.
13. Anchoring and Calibration:
- Calibration Procedures: Regular calibration and anchor maintenance are essential to ensure the accuracy of anchor nodes.
14. Geometric Configuration:
- Network Shape: The shape and layout of the network can affect the accuracy of localization techniques.
15. Error Mitigation:

- Error Correction: Techniques for error mitigation and outlier detection can improve localization results.

16. Deployment Strategies:

- Random vs. Deterministic Deployment: The choice of deployment strategy, whether random or deterministic, can influence the network's geometry and accuracy. Addressing these influencing factors and selecting appropriate localization techniques and algorithms based on the specific WSN application are crucial for achieving accurate and reliable node localization. Additionally, ongoing monitoring and maintenance are essential to maintain localization accuracy over time.

VI. NETWORK MODEL AND PROPAGATION MODEL

A. Network Model

A significant number of localization algorithms for Wireless Sensor Networks (WSNs) operate under the assumption that the network comprises anchor nodes and sensor nodes (referred to as unknown nodes), as illustrated in Fig. 12. Sensor nodes are dispersed randomly throughout the target sensing area and receive beacon messages transmitted by anchor nodes. The main role of anchor nodes is to broadcast anchor signals, enabling unknown sensor nodes to determine their respective locations. Each sensor node gathers RSSI information from anchor signals over a fixed period. WSNs models operate based on the following assumptions:

- The wireless network remains static post-deployment, with sensor nodes distributed randomly across a two-dimensional geographic area, thereby forming the wireless network. These nodes main 1tain fixed positions after deployment.
- A single Sink main node is positioned at a relatively stationary location outside the WSN, serving as the primary connection point to the main processing unit.
- The network comprises N static anchor nodes, whose positions are predetermined either through GPS or other methods, such as manual pre-programming during deployment, along with M unknown nodes.

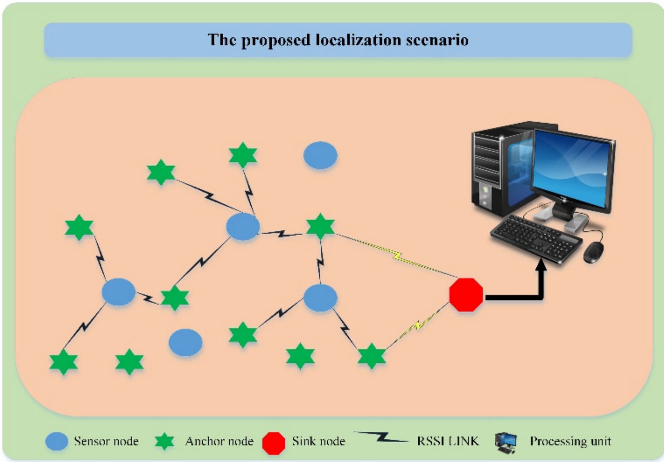

Fig. 12. Network model

B. Localization System Stages

The implementation of any localization system typically involves four distinct stages, as illustrated in Fig. 13:

- Distance Calculation Stage: This initial stage entails computing distances using various distance measurement techniques outlined in subsection 3.1. These techniques are paired with an appropriate radio propagation model that describes the relationship between distance and signal power.
- Position Calculation Stage: Following the distance calculation stage, this second stage focuses on estimating the positions of unknown nodes. Traditional approaches such as multilateration or angulation are commonly utilized for this purpose.
- Localization Algorithm: The pivotal stage in the localization system, where the information obtained from the previous stages is processed to estimate the positions of sensor nodes with high localization accuracy.
- Evaluation Stage: This final stage is dedicated to evaluating the effectiveness of the localization algorithm. It involves assessing various metrics such as localization error, localization rate percentage, and implementation time to give decide about the algorithm's performance.

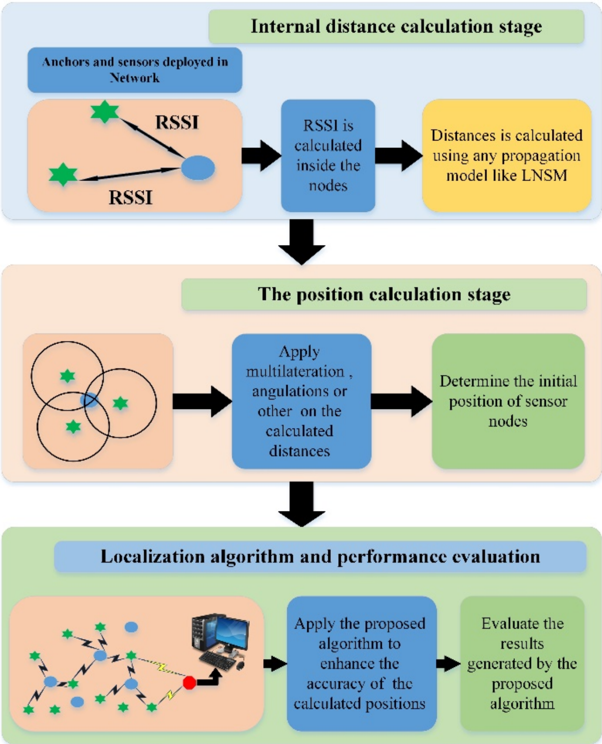

Fig. 13. Localization system stages

C. Radio Propagation Models

Propagation models elucidate how to forecast the average received signal strength (RSS) at a given distance from the transmitter, as well as the variability of signal strength in close spatial proximity to a specific location [5]. In scientific literature, and during 40 years, numerous studies have developed various models for propagation in indoor and outdoor environments [26] and [40]. When distance measurement techniques rely on RSSI, the Lognormal shadowing model (LNSM) is a suitable choice for propagation modeling. This selection is attributed to its simplicity and its close correspondence with the relationship between signal attenuation and distance, as depicted in Equation (2) in subsection 3.1.1.

Then the distance between unknown node and anchor node can be calculated as follows:

$$d = 10^{\frac{RSSI_{d_0} - RSSI_d + X_\sigma}{10n}} \qquad (6)$$

To determine the coordinates of any unknown node, it is necessary to obtain the distance between the unknown node and at least three anchors located under the coverage. Once the distances to three or more anchors are determined using Equation 6, the coordinates of the unknown node can be calculated through trilateration. It's important to acknowledge that in any ranging technique model, there will be measurement errors, commonly resulting from noisy range estimations in practical localization systems. The precision of the position estimation stage is greatly affected by these imprecise range measurements. Apart from geometric approaches like multilateration, alternative methods such as optimization techniques can be employed to minimize the calculation error in the coordinates of unknown nodes.

D. Objective Function Formulation

As previously mentioned, the primary objective of WSN localization algorithms is to determine the positions of unknown nodes using information about the positions of anchor nodes. This process can be defined as an optimization problem, with the objective function guiding the search for the most appropriate solution. Many metaheuristic optimization-based localization algorithms employ the circular positioning algorithm to formulate the objective function for solving the localization problem. The fundamental concept of this algorithm is to identify the (x, y) position of the unknown node that minimizes the sum of squared errors in the set of estimated distances. Let (X_i, Y_i) represent the position of anchor node i, where i, $(i = 1, 2. . . N)$ (N being the number of anchor nodes). The calculated distances (d_i) between an unknown node and anchor nodes are determined by the ranging model, assuming the use of the Lognormal Shadowing Model (LNSM). The squared error of the calculated distances is defined as follows:

$$\varepsilon = \frac{1}{N}\sum_{i=1}^{N}\left(\sqrt{(X_i - x)^2 + (Y_i - y)^2} - d_i\right)^2 \qquad (7)$$

Equation 7 is supposed as the objective function or the fitness function $f(x, y)$ as follows:

$$f(x,y) = \frac{1}{N}\sum_{i=1}^{N}\left(\sqrt{(X_i - x)^2 + (Y_i - y)^2} - d_i\right)^2 \qquad (8)$$

Where:

- $N \geq 3$ denotes the number of anchor nodes within the transmission range of unknown node.
- (X_i, Y_i) is the position's coordinate of ith anchor node.
- (x, y) is the position's coordinate of an unknown node.
- d_i is the calculated distance between one unknown node and anchor i.

VII. RELATED WORKS OF LOCALIZATION ALGORITHM BASED ON OPTIMIZATION TECHNIQUES

The literature contains various surveys focusing on Wireless Sensor Networks (WSNs), covering topics such as protocols, applications, and localization algorithms, which can be referenced in the following citations: [2], [41], [4], [42], [43], [44], [45], [46]. As mentioned earlier in this paper, there is a visible trend towards the adoption of optimization techniques over traditional estimation methods in the localization process. This shift is driven by the capability of optimization techniques to enhance localization accuracy, particularly in scenarios reliant on Received Signal Strength Indication (RSSI) measurements. In the field of WSN localization, optimization techniques have been extensively deployed, fostering valuable exploration aimed at improving accuracy within this field.

In [47], the authors devised an algorithm that utilized a mobile anchor, employing Ant Colony Optimization for path planning. Additionally, they implemented a centroid-weighted localization algorithm to estimate the positions of unknown nodes. Simulation results demonstrated that the proposed algorithm outperformed traditional centroid algorithms in terms of localization precision. In [48], the authors developed localization algorithms leveraging Genetic Algorithms to address the challenge of low positioning precision with minimal anchor nodes, achieving high accuracy. Simulation results indicated that only three anchor nodes were sufficient for optimal location estimation. In [49], the authors leveraged Ultra-Wideband (UWB) technology to enhance localization accuracy. Their evaluation was conducted through simulation, with results indicating satisfactory algorithm efficiency.

In [50], the authors utilized sunflower optimization (SFO) to improve localization accuracy, building upon the DV-HOP algorithm. Their results showcased a significant enhancement in localization accuracy compared to conventional methods. In [51], the authors employed the Nystrom method in conjunction with locally linear embedding (NLLE) to approximate node positions, introducing a novel technique to boost localization accuracy. Results indicated that the proposed NLLE algorithm achieved notably high localization accuracy, surpassing other compared algorithms by up to 30.02%. The comparison was conducted against MDS-AEKF and MDS-AUKF algorithms. Notably, the authors did not consider additional performance factors such as noise and localization time in their evaluation. In [52], the authors proposed a WSN localization approach based on a novel method called graph embedding with polynomial mapping (GEPM). They evaluated GEPM's performance across various factors including the number of anchors, communication range, and noise levels. Their findings suggested that GEPM can achieve high accuracy, particularly in smaller areas with low noise conditions.

In [53], the authors employed the Particle Swarm Optimization (PSO) algorithm for the localization process in WSNs. Through performance evaluation, they concluded that their PSO-based localization algorithm achieved higher accuracy compared to other algorithms that relied on simulated annealing. In [54], an enhanced version of the DV-Hop algorithm integrated PSO to improve localization accuracy. Simulation results demonstrated that this new iteration of the DV-Hop algorithm, enhanced by PSO, was notably effective compared to the traditional DV-Hop algorithm, achieving a high localization coverage rate.

In [55], the authors proposed leveraging basic PSO optimization techniques along with RSSI to enhance localization precision. They applied their approach similarly to the DV-distance method to improve localization success ratios. Experimental results and comparisons indicated that the proposed algorithm outperformed others in terms of both accuracy and node access ratio. In [56], the authors introduced a hybrid model that combines fuzzy logic and an Extreme Learning Machine with a Vector Particle Swarm Optimization, termed **HVP-FELM**, for localization. Their study focused solely on average localization error, considering factors such as communication range and the number of anchors. In the best case scenario, the localization error was approximately 1.5m. However, the authors did not evaluate the impact of noise on the localization process. In [57], the authors employed Cooperative Distributed Particle Swarm Optimization (CDPSO), a new version of PSO, to accurately determine node positions. Their study concluded that the proposed algorithm surpassed other localization algorithms in terms of localization error and complexity. However, the evaluation did not consider influencing factors such as the number of anchors or noise.

In [58], the authors introduced a modified rat swarm optimizer (MRSO) to enhance node localization in wireless sensor networks (WSNs). Comparative evaluations with the original RSO and other metaheuristic algorithms demonstrated that MRSO consistently outperformed them. Notably, MRSO significantly reduced the Average Localization Error (ALE) compared to RSO and other algorithms, achieving reductions of68.52% (RSO), 71.75% (bat optimization algorithm), 70.58% (BOA variant 1), and 66.81% (BOA variant 2).

The study in [59] introduces the Optimized Localization Learning Algorithm (OLLA) and evaluates its performance against established localization-based learning algorithms such as APIT, LAEP, RANN, and SPSO in both indoor and outdoor settings. Assessment metrics including absolute localization error, relative localization error, root mean square error, and anchor node probability distribution were utilized. The results demonstrate that OLLA exhibits robust performance in both environments. Furthermore, the paper provides a succinct comparison of various localization-based learning algorithms, highlighting their respective strengths and weaknesses.

In [60], the authors propose an enhanced particle swarm optimization algorithm named "Improved Self Adaptive Inertia Weight Particle Swarm Optimization (ISAPSO)" for wireless sensor network (WSN) localization. ISAPSO is designed based on the convergence conditions and initial search space characteristics of the PSO algorithm. Comparative evaluation with two other PSO-based location estimation algorithms illustrates that ISAPSO outperforms its counterparts in terms of positioning accuracy, power consumption, and real-time performance across diverse scenarios, including variations in beacon node proportions, node densities, and ranging errors.

In [61], the authors introduced HADENM, an advanced algorithm that combines adaptive differential evolution (ADE) and Nelder-Mead (NM) methods to estimate passive target positions. HADENM incorporates adaptive parameter updates in ADE to balance global and local optimization and leverages NM to enhance exploitation. Simulation results demonstrate HADENM's capability to achieve the Cramer-Rao lower bound (CRLB) and outperform constrained weighted least squares (CWLS) and differential evolution (DE) algorithms. These findings underscore HADENM's accuracy and robustness for localization processes across various noise levels.

In [62], the authors proposed FPSOTS, a novel approach for localization in Wireless Sensor Networks (WSN) using optimization techniques. FPSOTS improves upon the Particle Swarm Optimization (PSO) method by integrating tabu search to expedite convergence towards enhanced solutions. By employing the Received Signal Strength Indicator (RSSI) method for inter-sensor distance assessment, FPSOTS is evaluated via Matlab simulations. The authors concluded that FPSOTS achieves rapid convergence and superior accuracy compared to other approaches, surpassing HPSOVNS, NS-IPSO, ECS-NL, and GTOA by 40%, 35%, 44%, and 22%, respectively.

In [63], the authors introduced two distinct localization and tracking estimation methods designed for Wireless Sensor Networks (WSNs). The first method follows a conventional approach, relying on the Long Normal Shadowing Method (LNSM), while the second approach utilizes a hybrid **PSO-GRNN** (Particle Swarm Optimization - Generalized Regression Neural Network) algorithm. By combining PSO with GRNN, the hybrid algorithm optimizes the spread constant (σ) to enhance localization accuracy significantly. Comparative performance evaluations against the conventional LNSM-based approach and previous algorithms used in related studies revealed that the hybrid **PSO-GRNN** algorithm outperforms the traditional LNSM method by achieving notably lower Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) scores. This addresses the significant localization errors observed with the traditional LNSM method.

In [64], the authors proposed an enhanced DV-Hop localization algorithm based on Selective Opposition Class Topper Optimization (SOCTO). This algorithm focuses on optimizing the computation of the average hop size with the weight of beacon nodes to reduce localization errors within the estimated distance between the beacon and the unknown node. Results demonstrate that the proposed approach outperforms the basic DVHop technique and related techniques in terms of average localization error. In [54], the authors employed the basic PSO approach and utilized Received Signal Strength Indicator (RSSI) to enhance localization precision in WSNs. Their algorithm, implemented similarly to DV-Hop distance, further improves localization success rates. Experimental results and comparisons indicate that the proposed approach exhibits better performance in terms of localization accuracy and node access ratio. Other works utilizing the basic version of PSO to refine accuracy can be found in papers [65], [66], and [3].

In [67], the authors introduced three variants of the Naked Mole-Rat Algorithm (NMRA) designed to enhance its exploration and exploitation capabilities. These variants were evaluated using the CEC 2019 benchmark functions, serving as benchmarks for comparison against the foundational NMRA. Results demonstrated that the proposed NMRA variants exhibit rapid convergence and yield optimal solutions across a majority of the benchmark functions. Moreover, the suggested NMRA variant outperforms existing localization solutions, demonstrating superior performance in terms of localization error for both 2D and 3D environments. These findings underscore the enhanced capabilities of the proposed NMRA variants and their potential applicability in optimization and localization scenarios. In [68], the authors proposed two variants of the bat optimization algorithm (BOA) aimed at improving the efficiency of sensor node localization by addressing limitations of the original BOA, particularly its susceptibility to local optimum solutions. Modifications in BOA variants 1 and 2 enhance exploration and exploitation features through improved global and local search strategies. Extensive simulations with varying numbers of target and anchor nodes were conducted to evaluate their performance. Results showed that both proposed variants outperform other algorithms in mean localization error, number of localized nodes, and localization time. A detailed comparative analysis revealed that BOA variant 2 excels in various error metrics and localization efficiency, making it more effective than variant 1, the original BOA, and other existing optimization algorithms.

In paper [69], the authors introduced a novel approach called the Centroid Localization Algorithm based on the Social Spider Optimization Algorithm (CLA-SSO). This method aims to improve the localization capabilities of the basic Centroid Localization Algorithm (CLA), which is a range-free localization technique. The CLA-SSO method integrates the Social Spider Optimization metaheuristic (SSO) to optimize the initial spider locations obtained from CLA. Through extensive simulations, the authors systematically varied parameters such as transmission radius, anchor node ratio, and the number of unknown nodes. The results indicated that the CLA-SSO algorithm outperforms the basic CLA in terms of localization accuracy.

In paper [70], a novel range-free localization solution for wireless sensor networks was presented by the authors. This approach combines geometric constraint and hop progress-based methods. It categorizes anchor node pairs and utilizes geometric information to determine the position of target or unknown nodes, addressing challenges posed by anisotropic factors in various WSN topologies. Leveraging the Jaya algorithm and a range free method for selecting reliable anchor pairs, the proposed approach was compared with existing methods like DV-max Hop, PSO, and QSSA-based localization algorithms. The results demonstrated enhanced localization accuracy, particularly with varying anchor nodes and node density, while considering factors like irregularity and computation time.

In [71], a novel and cost-effective localization solution utilizing Unmanned Aerial Vehicles (UAVs) was introduced by the authors. They optimized the flying altitude to define node localization as a least square optimization problem, considering the impact of UAV altitude on accuracy. Addressing limitations in classical multilateration with received signal strength indicators, the study advocates for least square localization employing optimization techniques. Specifically, the authors utilized the Artificial Bee Colony (ABC) algorithm to optimize UAV anchors, aiming to minimize localization error. Through comprehensive simulation analysis, the effectiveness of the ABC localization scheme for enhanced accuracy in UAV-based localization was demonstrated.

In [72], the **RA-GN** algorithm was implemented within a localization system, and experimental evaluations were conducted using data from a measurement campaign in a semi-forest test field. The study also examined the effects of rotating the tag, representing the vehicle, and observed changes in position estimation accordingly. By conducting a comparative analysis of root mean square error metrics against a commercial system, the authors found that the **RA-GN** algorithm significantly improves accuracy, particularly in real and crowded environments. They showed that the proposed algorithm remains effective even in challenging scenarios with signal perturbations caused by obstacles and variations in the angular positions of the tag relative to the anchors. Other works employing optimization techniques to enhance accuracy are documented in references [73], [74], [75], [76] and [77].

VIII. SUMMARY AND CONCLUSIONS

This paper extensively explored key approaches to localizing wireless sensor networks, employing various techniques encompassing both anchor-free and anchor dependent methodologies. The discussion spanned distributed and centralized techniques, offering a comprehensive examination of the entire localization loop. The paper delved into the limitations that hinder the efficiency of position techniques, shedding light on the importance, advantages, and disadvantages of these approaches. Techniques such as Received Signal Strength Indication (RSSI), Time of Arrival (TOA), Angle of Arrival (AoA), and Optimization techniques were scrutinized, providing a nuanced understanding of their applications and implications. Acknowledging the limitations resulted from the manufacturing constraints on sensor devices and the precision required for localization in Wireless Sensor Network (WSN) applications, particularly those dependent on distance calculation, Centralized localization schemes based on Received Signal Strength Indication (RSSI) were appointed as a cost-effective and satisfactory solution. However, the RSSI technique is not without its shortcomings, notably in terms of low measurement accuracy. To address this drawback, numerous researchers have strategically employed optimization techniques to achieve heightened accuracy in WSN localization. This paper aimed to illuminate various optimization techniques utilized for enhancing measurement accuracy and underscore the merits associated with their implementation.

This paper concluded that optimization techniques exhibit high efficiency and the ability to address the issue of low measurement accuracy associated with RSSI technology. Additionally, it asserted that each optimization technique has its own set of advantages and disadvantages that differ from those of other techniques. Therefore, one can leverage the advantages and mitigate the shortcomings by integrating these technologies to create a hybrid solution, as demonstrated in several works mentioned in the literature review.

This paper offered researchers a comprehensive understanding of a localization algorithm based on optimization techniques for locating nodes in outdoor environments. This empowers researchers to develop valuable algorithms that employ either a single optimization technique or combine these strategies to create hybrid algorithms. The overarching objective of these algorithms is to precisely determine the locations of nodes in WSNs, thereby ensuring effective data transmission without interruptions in the network.

For future work, our plan is to conduct a review focusing on optimization techniques-based localization algorithms, specifically in indoor environments instead of outdoor ones. Additionally, we aim to explore localization algorithms that leverage neural network approaches and artificial intelligence.

ACKNOWLEDGMENT

We would like to express our sincere gratitude to our supervisor, Prof. Dr. ADAMU ABUBAKAR IBRAHIM, for his valuable guidance and support throughout the research process. His expertise and insights were invaluable in shaping our research and helping us to overcome challenges.

CONFLICTS OF INTEREST

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

REFERENCES

[1] P. S. Perumal and V. R. Uthariaraj. (2012). Novel Localization of Sensor Nodes in Wireless Sensor Networks using Co-Ordinate Signal Strength Database. *Procedia Eng.*, *30*, 662–668. Doi: http://dx.doi.org/10.1016/j.proeng.2012.01.912.

[2] N. Aggarwal, N. Sharma, and Y. Bhale. (2022). Performance Analysis of Power Efficient Routing Protocols for Wireless Sensor Networks: A Survey. *2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE)*, 270–274. Doi: 10.1109/ICACITE53722.2022.9823426.

[3] S. Singh, S. Shivangna, and E. Mittal. (2013). Range based Wireless Sensor Node Localization Using PSO and BBO and Its Variants. *2013 Int. Conf. Commun. Syst. Netw. Technol.*, 309–315. Doi: 10.1109/CSNT.2013.72.

[4] S. Kagi and B. S. Mathapati. (2021). Localization in Wireless Sensor Networks: A Compact Review on State-of-the-Art models. *2021 6th International Conference on Inventive Computation Technologies (ICICT)*, 5–12. Doi: 10.1109/ICICT50816.2021.9358793.

[5] M. Marks and E. Niewiadomska-szynkiewicz. (2011). Self-adaptive Localization using Signal Strength Measurements. *SENSORCOMM 2011 Fifth Int. Conf. Sens. Technol. Appl.*, 73–78,

[6] J. Hu, J. Luo, Y. Zhang, P. Wang, and Y. Liu. (2015). Location-based Data Aggregation in 6LoWPAN. *Int. J. Distrib. Sens. Networks*, *2015*(4). Doi: 10.1155/2015/912926.

[7] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci. (2002). Wireless Sensor Networks: A Survey. *Comput. Networks*, *38*(4), 393–422. Doi: 10.1016/S1389-1286(01)00302-4.

[8] V. Rajaravivarma, Y. Yang, and T. Yang. (2003). An Overview of Wireless Sensor Network and Applications. *Syst. Theory Proc. Southeast. Symp.*, 432–436.

[9] V. Ovidiu. (2011). Internet of Things - Global Technological and Societal Trends.

[10] R. H. Weber and R. Weber. (2010). *Internet of Things: Legal Perspectives*. Springer Publishing Company, Incorporated.

[11] L. Atzori, A. Iera, and G. Morabito. (2010). The Internet of Things: A Survey. *Comput. Networks*, *54*(15), 2787–2805.

[12] Z. Chen, X. Feng, T. Huang, F. Bu, and H. Wang. (2013). A Localization Method for the Internet of Things. *J. Supercomput.*, *63*(3), 657–674.

[13] D. K. Kim, Y. S. Kim, and J. W. B. T.-I. C. on U. I. M. and C. Chong. (2011). Hybrid RSS/TOA Wireless Positioning with a Mobile Anchor in Wireless Sensor Networks, 25–32.

[14] S. Haller, S. Karnouskos, and C. Schroth. (2008). The Internet of Things in an Enterprise Context. *Nihon Kyukyu Igakukai Zasshi*, *20*(11), 871–881.

[15] N. Patwari, A. O. Hero, M. Perkins, N. S. Correal, and R. J. O'Dea. (2003). Relative location Estimation in Wireless Sensor Networks. *IEEE Trans. Signal Process.*, *51*(8), 2137–2148,

[16] K. Whitehouse, C. Karlof, A. Woo, F. Jiang, and D. B. T.-I. S.

on I. P. in S. N. Culler. (2005). The Effects of Ranging Noise on Multihop Localization: An Empirical Study, 10.

[17] D. Niculescu and B. Nath. (2002). Ad Hoc Positioning System (APS) Using AoA. *Proc. - IEEE INFOCOM*, *3*(2), 1734–1743.

[18] D. Madiganl, E. Einahrawy, R. P. Martin, W. H. Ju, P. Krishnan, and A. S. Krishnakumar. (2005). Bayesian Indoor Positioning Systems. *Proc.-IEEE INFOCOM*, *2*, 1217–1227.

[19] E. Elnahrawy, X. Li, and R. P. B. T.-S. and A. H. C. and N. Martin (2004). The Limits of Localization using Signal Strength: A Comparative Study. *2004 First IEEE Communications Society Conference on*. *2004*, 406–414.

[20] P. Bergamo and G. B. T.-T. I. I. S. on P. Mazzini. (2002). Localization in Sensor Networks with Fading and Mobility. *Indoor and Mobile Radio Communication*s, *2*, 750–754.

[21] Rappaport and Theodore. (2001). Wireless Communications: Principles and Practice, *8*(1), 33–38.

[22] R. Al Alawi. (2011). RSSI based Location Estimation in Wireless Sensors Networks, 118–122. Doi: 10.1109/ICON.2011.6168517.

[23] T. S. Rappaport, J. Reed, and B. D. Woerner. (1996). Position Location using Wireless Communications on Highways of the Future. *IEEE Commun. Mag.*, *34*(10), 33–41.

[24] B. Liu, L. Wang, and Y. H. Jin. (2007). An Effective PSO-Based Memetic Algorithm for Flow Shop Scheduling. *IEEE Trans. Syst. Man Cybern. Part B Cybern. A Publ. IEEE Syst. Man Cybern. Soc.*, *37*(1), 18–27.

[25] K. Pahlavan, X. Li, and J. P. Makela. (2002). *Indoor Geolocation Science and Technology*. IEEE Press.

[26] F. Xiao, M. Wu, H. Huang, R. Wang, and S. Wang. (2012). Novel Node Localization Algorithm based on Nonlinear Weighting Least Square for Wireless Sensor Networks. *Int. J. Distrib. Sens. Networks*, *2012*, 1–6. Doi: 10.1155/2012/803840.

[27] J. Luo, J. Hu, D. Wu, and R. Li. 2015. Opportunistic Routing Algorithm for Relay Node Selection in Wireless Sensor Network, *IEEE Trans. Ind. Informatics*, *11*(1), 112–121.

[28] W. Cao, H. Wang, and L. Liu. (2014). An Ant Colony Optimization Algorithm. *4*(3), 299–309.

[29] R. Malhotra, N. Singh, and Y. Singh. (2011). Genetic Algorithms: Concepts, Design for Optimization of Process Controllers, 4(2), 39–54.

[30] A. Savvides, H. Park, and M. B. Srivastava. (2002). The Bits and Flops of the n-hop Multilateration Primitive for Node Localization Problems. *Proceedings of the 1st ACM International Workshop on Wireless Sensor Networks and Applications*, 112–121. Doi: 10.1145/570738.570755.

[31] I. Amundson, J. Sallai, X. Koutsoukos, and A. Ledeczi. (2010). Radio Interferometric Angle of Arrival Estimation. *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, *5970*, 1–16. Doi: 10.1007/978-3-642-11917-0_1.

[32] H. Jia, Y. Wang, and X. B. T.-I. C. on I. C. and I. S. Tao. (2010). Localization Algorithm for Mobile Anchor Node based on Genetic Algorithm in Wireless Sensor Network. 40–44.

[33] Y. Wang, J. Hang, C. Li, J. You, S. Chen, and L. Cheng. (2018). A Mobile Localization Method for Wireless Sensor Network in Mixed LOS/NLOS Environments. *2018 8th International Conference on Electronics Information and Emergency Communication (ICEIEC)*, 87–90. Doi: 10.1109/ICEIEC.2018.8473467.

[34] Jaya and A. Payal. (2018). Analysis and Implementation of APIT Localization Algorithm for Wireless Sensor Network. *2018 3rd International Conference on Computer and Communication Systems (ICCCS)*, 310–313. Doi: 10.1109/CCOMS.2018.8463241.

[35] S.-H. Lee, C.-H. Cheng, C.-C. Lin, and Y.-F. Huang. (2023). PSO-based Target Localization and Tracking in Wireless Sensor Networks. *Electronics*, 12(4). Doi: 10.3390/electronics12040905.

[36] Q. Ren, Y. Zhang, I. Nikolaidis, J. Li, and Y. Pan. (2020). RSSI Quantization and Genetic Algorithm based Localization In Wireless Sensor Networks. *Ad Hoc Networks*, *107*, 102255, Doi: https://doi.org/10.1016/j.adhoc.2020.102255.

[37] H. S. Hosseini. (2007). Problem Solving by Intelligent Water Drops. *IEEE Congr. Evol. Comput. Singapore*, 3226–3231. Doi: 10.1109/CEC.2007.4424885.

[38] L. Wu, X. Huang, J. Cui, C. Liu, and W. Xiao. (2023). Modified Adaptive Ant Colony Optimization Algorithm and its Application for Solving Path Planning of Mobile Robot. *Expert Syst. Appl.*, *215*, 119410. Doi: https://doi.org/10.1016/j.eswa.2022.119410.

[39] B. F. Gumaida and J. Luo. (2019). A Hybrid Particle Swarm Optimization with a Variable Neighborhood Search for the Localization Enhancement in Wireless Sensor Networks. *Appl. Intell.*, *49*, 3539–3557.

[40] R. V. Kulkarni and G. K. Venayagamoorthy. (2011). Particle Swarm Optimization in Wireless-sensor Networks: A Brief Survey. *IEEE Trans. Syst. Man, Cybern. Part C (Applications Rev.*, 41(2), 262–267. Doi: 10.1109/TSMCC.2010.2054080.

[41] A. A and A. Davidson. (2022). A Comparative Analysis of Localization Techniques in Wireless Sensor Network. *2022 IEEE International Conference on Signal Processing, Informatics, Communication and Energy Systems (SPICES)*, 285–289. Doi: 10.1109/SPICES52834.2022.9774208.

[42] T. Arampatzis, J. Lygeros, and S. Manesis. (2005). A Survey of Applications of Wireless Sensors and Wireless Sensor Networks. *Proc. 2005 IEEE Int. Symp. on, Mediterrean Conf. Control Autom. Intell. Control. 2005*, 719–724, Doi: 10.1109/.2005.1467103.

[43] I. Amundson and X. Koutsoukos. (2009). A Survey on Localization for Mobile Wireless Sensor Networks. *Mob. Entity Localization Track.* 235–254. Doi: 10.1007/978-3-642-04385-7_16.

[44] G. Mao, B. Fidan, and B. Anderson. (2007). Wireless Sensor Network Localization Techniques. *Comput. Networks*, *51*(10), 2529–2553. Doi: 10.1016/j.comnet.2006.11.018.

[45] M. Perillo, W. Heinzelman, J. Yick, B. Mukherjee, and D. Ghosal. (2004). Wireless Sensor Network Protocols. *Comput. Networks*, *52*(12), 2292–2330. Doi: 10.1016/j.comnet.2008.04.002.

[46] P. Rawat, K. D. Singh, H. Chaouchi, and J. M. Bonnin. (2014). Wireless Sensor Networks: A Survey on Recent Developments and Potential Synergies. *J. Supercomput.*, *68*(1), 1–48. Doi: 10.1007/s11227-013-1021-9.

[47] Y. H. Lu and M. Zhang. (2014). Adaptive Mobile Anchor Localization Algorithm based on Ant Colony Optimization in WirelESS. *Int. J. SMART Sens. Intell. Syst.*, *7*(4), 1943–1961.

[48] K. Uraiya and D. K. Gandhi. (2014). Genetic Algorithm for Wireless Sensor Network with Localization Based Techniques. *Int. J. Sci. Res. Publ.*, *4*(9), 1–6.

[49] Q. Cheng. (2021). A Robust Indoor Localization Algorithm for WSN in LOS and NLOS Environment. *2021 IEEE 11th International Conference on Electronics Information and Emergency Communication (ICEIEC)*, 91–94. Doi: 10.1109/ICEIEC51955.2021.9463824.

[50] V. C. S. R. Rayavarapu and A. Mahapatro. (2021). A Novel Range-free Anchor-free Localization in WSN Using Sun Flower Optimization Algorithm. *2021 Advanced Communication Technologies and Signal Processing (ACTS)*,

1–6. Doi: 10.1109/ACTS53447.2021.9708099.

[51] N. Jain, S. Verma, and M. Kumar. (2018). Low Cost Localization using Nyström Extended Locally Linear Embedding. *Pattern Recognit. Lett.*, *110*.

[52] H. Xu, H. Sun, Y. Cheng, and H. Liu. (2016). Wireless Sensor Networks Localization based on Graph Embedding with Polynomial Mapping. *Comput. Networks*, *106*, 151–160.

[53] L. Jacob. (2008). Localization in Wireless Sensor Networks Using Particle Swarm Optimization. *IET Conf. Proc.*, 227–230. http://digital-library.theiet.org/content/conferences/10.1049/cp_20080185

[54] F. Zhang. (2013). Positioning Research for Wireless Sensor Networks based on PSO Algorithm. *20220744*, 7–10.

[55] P. Chuang. (2011). Employing PSO to Enhance RSS Range-based Node Localization for Wireless Sensor Networks. *J. Inf. Sci.*, *1611*, 1597–1611.

[56] S. Phoemphon, C. So-In, and D. Niyato. (2018). A Hybrid Model using Fuzzy Logic and an Extreme Learning Machine with Vector Particle Swarm Optimization for Wireless Sensor Network Localization. *Appl. Soft Comput.*, 65.

[57] R. Janapati, C. Balaswamy, and K. Soundararajan. (2018). Enhancement of Localized Routing Using CDPSO in WSN. *2018 Conference on Signal Processing And Communication Engineering Systems, SPACES 2018*, 16–19. Doi: 10.1109/SPACES.2018.8316306.

[58] O. Alfawaz, W. Osamy, M. Saad, and A. M. Khedr. (2023). Modified Rat Swarm Optimization Based Localization Algorithm for Wireless Sensor Networks. *Wirel. Pers. Commun.*, *130*(3), 1617–1637. Doi: 10.1007/s11277-023-10347-x.

[59] P. Yadav, S. C. Sharma, O. Singh, and V. Rishiwal. (2023). Optimized Localization Learning Algorithm for Indoor and Outdoor Localization System in WSNs. *Wirel. Pers. Commun.*, *130*(1), 651–672. Doi: 10.1007/s11277-023-10304-8.

[60] Q. Yang. (2022). A new Localization Method based on Improved Particle Swarm Optimization for Wireless Sensor Networks. *IET Softw.*, *3*(16).

[61] M. B. Rosić, M. I. Simić, and P. V Pejović. (2020). Passive target Localization Problem based on Improved Hybrid Adaptive Differential Evolution and Nelder-Mead Algorithm. *J. Sensors*, *2020*, 1–20.

[62] E. Tagne Fute, D.-K. Nyabeye Pangop, and E. Tonye. (2023). A New Hybrid Localization Approach in Wireless Sensor Networks based on Particle Swarm Optimization and tabu Search. *Appl. Intell.*, *53*(7), 7546–7561. Doi: 10.1007/s10489-022-03872-y.

[63] S. M. Tariq and I. S. Al-Mejibli. (2023). WSN Localization Method based on Hybrid PSO-GRNN Approach. *Int. J. Intell. Eng. Syst.*, *16*(5).

[64] T. K. Mohanta and D. K. Das. (2023). Improved Wireless Sensor Network Localization Algorithm Based on Selective Oppositio*n Class Topper Optimization (SOCTO). Wirel. Pers. Commun.,* *128*(4), 2847–2868. Doi: 10.1007/s11277-022-10075-8.

[65] K. S. Low, H. a Nguyen, and H. Guo. (2008). A Particle Swarm Optimization Approach for the Localization of a Wireless Sensor Network. *2008 IEEE Int. Symp. Ind. Electron.*, 1820–1825. Doi: 10.1109/ISIE.2008.4677205.

[66] K. S. Low, H. A. Nguyen, and H. Guo. (2008). Optimization of Sensor Node Locations in a Wireless Sensor Network. *2008 Fourth Int. Conf. Nat. Comput.*, *5*, 286–290. Doi: 10.1109/ICNC.2008.670.

[67] P. Singh, N. Mittal, U. Singh, and R. Salgotra. (2021). Naked Mole-Rat Algorithm with Improved Exploration and Exploitation Capabilities to Determine 2D and 3D Coordinates of Sensor Nodes in WSNs. *Arab. J. Sci. Eng.*, *46*(2), 1155–1178. Doi: 10.1007/s13369-020-04921-9.

[68] S. S. Mohar, S. Goyal, and R. Kaur. (2022). Localization of Sensor Nodes in Wireless Sensor Networks using Bat Optimization Algorithm with Enhanced Exploration and exploitation Characteristics. *J. Supercomput.*, *78*(9), 11975–12023. Doi: 10.1007/s11227-022-04320-x.

[69] Z. Lalama, F. Semechedine, N. Giweli, and S. Boulfekhar. (2023). Social Spider Optimization Meta-heuristic for Node Localization Optimization in Wireless Sensor Networks BT - Proceedings of the Second International Conference on Innovations in Computing Research (ICR'23). K. Daimi and A. Al Sadoon, Eds., Cham: Springer Nature Switzerland, 381–391.

[70] Shilpi and A. Kumar. (2023). A Localization Algorithm using Reliable Anchor Pair Selection and Jaya Algorithm for Wireless Sensor Networks. *Telecommun. Syst.*, *82*(2), 277–289. Doi: 10.1007/s11235-022-00984-1.

[71] V. Annepu and A. Rajesh. (2020). Implementation of an Efficient Artificial Bee Colony Algorithm for Node Localization in Unmanned Aerial Vehicle Assisted Wireless Sensor Networks. *Wirel. Pers. Commun.*, *114*(3), 2663–2680. Doi: 10.1007/s11277-020-07496-8.

[72] L. A. Arellano-Cruz, G. M. Galvan-Tejada, and R. Lozano. (2022). Position Estimation using the Radical Axis Gauss Newton Algorithm: Experimental Analysis. *J. Intell. Robot. Syst.*, *107*(1), 2. Doi: 10.1007/s10846-022-01779-x.

[73] S. K. Gottapu and V. Appalaraju. (2018). Cognitive Radio Wireless Sensor Network Localization in an Open Field. *2018 Conference on Signal Processing And Communication Engineering Systems (SPACES)*, 45–48. Doi: 10.1109/SPACES.2018.8316313.

[74] F. Xiao, W. Liu, Z. Li, L. Chen, and R. Wang. (2018). Noise-Tolerant Wireless Sensor Networks Localization via Multinorms Regularized Matrix Completion. *IEEE Trans. Veh. Technol.*, *67*(3), 2409–2419. Doi: 10.1109/TVT.2017.2771805.

[75] A. Alomari, W. Phillips, N. Aslam, and F. Comeau. (2017). Swarm Intelligence Optimization Techniques for Obstacle-Avoidance Mobility-Assisted Localization in Wireless Sensor Networks. *IEEE Access*, *PP*(99), 1.

[76] J. Li *et al.* (2018). PSOTrack: A RFID-based System for Random Moving Objects Tracking in Unconstrained Indoor Environment. *IEEE Internet Things J.*, *PP*(99), 1.

[77] C. Shih. (2018). The Improvement of Indoor Localization Precision through Partial Least Square (PLS) and Swarm (PSO) Methods. *IEEE Instrum. Meas. Soc.*