OPTIMIZED ULTRA-WIDE BAND INDOOR POSITIONING TECHNOLOGIES FOR WSNs

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DECLARATION

I, hereby declared that the presented work in the thesis entitled **"OPTIMIZED ULTRA-WIDEBAND INDOOR POSITIONING TECHNOLOGIES FOR WSNs"** in fulfilment of degree of Doctor of Philosophy (Ph.D.) is outcome of research work carried out by me under the supervision **Dr. Parulpreet Singh**, working as **Associate Professor** in the **Electronics & Communication Engineering Department** of Lovely Professional University, Punjab, India. In keeping with general practice of reporting scientific observations, due acknowledgements have been made whenever work described here has been based on findings of other investigator. This work has not been submitted in part or full to any other University or Institute for the award of any degree.

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CERTIFICATE

This is to certify that the work reported in the Ph.D. thesis entitled **"OPTIMIZED ULTRA-WIDEBAND INDOOR POSITIONING TECHNOLOGIES FOR WSNs"** Submitted in fulfillment of the requirement for the reward of degree of **Doctor of Philosophy (Ph.D.)** in

the **Electronics & Communication Engineering Department** is a research work carried out by **Yedida Venkata Lakshmi** Registration No.**41900482**, is bonafide record of his/her original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course

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ABSTRACT

Localization in wireless sensor networks always a challenging task, many applications need localization with higher accuracy mainly military zones. The complexity in node localization becoming costly UWB based WSN having its advantage. Discovering the origin of a signal in a WSN is crucial for several applications, including navigational systems, civil/military monitoring, and emergency services. Many times, sensors are placed in inhospitable and distant places like mountains and deserts, where they are at risk of being destroyed. They are especially vulnerable to physical, electronic, and software attacks, as they are not easily accessible and difficult to protect. In order to design appropriate security mechanisms for wireless communication technology, it is very significant to understand security challenges and issues. Improving WSN technical characteristics without increasing cost criteria through technology development is a possibility. Some research aims to enhance existing WSNs &characteristics and technologies and expand their applications. An energy-efficient method for positioning sensor nodes is to develop protocols for improving reliability and sustainability against interference algorithms for distributed data processing. To fulfill the functional needs of WSNs, platforms either from scratch or already in existence must be selected. Each hardware platform provides sensor node parameters. Anchor nodes are highly-resourced wireless nodes known to have specific locations in modern WSNs. Target nodes are low-resource wireless nodes known for unknown locations. ANs (Anchor nodes) can be located by GPS or predetermined locations during network deployment. TNs (Target nodes) can be located based on these known locations and estimated ranges/angles. WSNs have attracted researchers and industry representatives for twenty years. Wireless technology based on the ultra-wide band (UWB) has been recognized as a feasible option. Wireless sensor networks (WSNs) have a lot of potential uses because of their high time-domain resolution, which allows them to do things like pinpoint location and tracking, work in tandem with current ultra-wide band systems (thanks to their incredibly low power spectral density), and provide a low-cost and energy-efficient way to implement technologies on-chip. The small devices known as anchor nodes (sensors) are usually built on microcontrollers and serve as the foundation of these types of networks. These nodes are typically powered by batteries that provide limited processing power. Consequently, the industrial and

government sectors have developed UWB-based sensor network concepts. One sub-gigahertz band (250–750 MHz), one low band (3.1–5 GHz), and one high band (6–10.6 GHz) are all open to ultra-wideband devices. Devices do not interact with one another across UWB bands; instead, each band has a single required channel. For WSN applications utilizing spread spectrum techniques, we go across the low band of UWB (3.244-4.742 GHz). The ease of use is the primary characteristic of the system, which relies on non- coherent detection and basic binary modulation techniques. It is the primary objective of this research to investigate how node localization measurements can be performed in WSN before optimal techniques are implemented. In a range-based environment, two methods were implemented, namely least squares and tetrahedrons. The solution to this problem is a new way for localizing sensor nodes that uses range-based localization techniques. A maximum probability distribution function expresses the problem. It has been suggested to employ the Chan method in conjunction with an RSSI-based TDOA measurement model in order to determine the locations of unknown nodes. We present a novel idea of projecting anchor nodes in a range-based environment by using particle swarm optimization (PSO), PSO with ensemble learning (EL-PSO) and back propagation neural networks (BPNN-PSO). Range-based non-collaborative isotropic WSN is implemented for 2D and 3D measurements with low UWB. Four anchor nodes which can locate the mobile nodes in indoor environments to improve location accuracy with maximum and minimum localization error calculated using above optimal techniques is the secondary contribution part of thesis. To prove their efficacy, the suggested methods are compared in terms of scalability, localization accuracy, and the number of nodes localised. By making use of RSSI, the algorithm was able to decrease the power consumption needed by the sensor node positioning system. The target and anchor node distances were calculated using this. The hybrid algorithm also outperformed PSO in terms of convergence speed.

The DV-Hop approach, which is applicable to large-scale applications, has an inclusion as range-free localization with UWB research advances. Also, using Mat-lab simulations, we compared the methods and error optimization accuracy. A packet distance is determined by the number of routers it must traverse; each router is considered a hop in distance-vector routing algorithms. Every 30 seconds, these protocols update every neighbour with the whole routing table. The distance can be determined by counting the number of routers a packet must pass through on its way to its final destination, a measure known as the hop count. The DV-Hop algorithms (Distance Vector routing) practicality, low cost, lack of hardware requirements, and ease of usage make it useful in different applications. The DV-Hop approach is still problematic for localization to a considerable degree. The Time Difference of Arrival (TDOA) technique can be used to determine the separation between several radio transmitters and a single receiver. To avoid early mistakes, the most accurate 2D and 3D initial measuring procedures include a Kalman filter and DV-Hop. We utilized a more precise technique to gauge the placement of beacons within the range-free specified region, and we calculated the localization error using the nodes, dynamic momentum. While it has its uses, the distance between unknown and anchor nodes is often inaccurate since its distance estimation of the average hop size isn't perfect. Errors in the estimated distances between sensor nodes also lead to erroneous localization. As a starting point for developing methods to minimize localization error, this range-free scenario makes use of the DV-Hop algorithm and particle swarm optimization. The performance of the algorithms was tested by measuring both the communication range and the number of anchor nodes. Since all anchor nodes remain stationary, it has been observed that mobile node placement uses less energy. Improving the original DV-Hop algorithm with online sequential DV-Hop required three stages. Additionally, to optimize the starting placements of unknown nodes and find a solution for the nonlinear equations, a hybrid approach combining PSO and EM-PSO was utilized. Despite its benefits, its distance estimate of the average hop size is prone to inaccuracies, making the distance between unknown nodes and anchor nodes erroneous. Additionally, inaccurate localization is caused by mistakes in the calculated distance between sensor nodes. As a starting point for developing methods to minimize localization error, this range-free scenario makes use of the DV-Hop algorithm and particle swarm optimization. Measuring the communication range and the number of anchor nodes allowed us to test the algorithm's performance. There is a noticeable decrease in energy consumption when mobile nodes are used instead of permanent anchor nodes. Using online sequential DV-Hop to improve the original DV-Hop algorithm was a three-stage process. Also, a hybrid method integrating PSO and EM-PSO was used to optimize the initial placements of unknown nodes and solve the nonlinear equations. The current study proposes an optimization strategy based on the ensemble method EM-PSO and hybrid HOP algorithms. In terms of localization error reduction, the current method outperforms traditional DV-HOP, according to the results. Lastly, compared to other state-of-the-art existing procedures, a variation of 15% is noted, and an inaccuracy below 2% is achieved after numerous sessions. When compared to standard algorithms, the localization accuracy provided by the suggested methods is much higher. The latest localization algorithms utilise the most effective techniques for reducing the error value. In comparison to comparable designs, the localization error distance is nearly 2.7 cms. We observe that there is a marked decrease.

Specific abstract

The core of the work explores different localization methods, including range-based techniques like least squares, tetrahedrons, and Chan's method, as well as range-free approaches like DV-Hop. It introduces novel optimization strategies using Particle Swarm Optimization (PSO), Ensemble Learning PSO (ELPSO), and Back Propagation Neural Networks (BPNN-PSO) to enhance localization accuracy. The research aims to minimize localization errors, particularly in 2D and 3D indoor environments with low UWB, using four anchor nodes to locate mobile nodes. The work also addresses the limitations of traditional methods, such as the inaccuracy of hop size estimation in DV-Hop, and proposes hybrid algorithms and advanced filtering techniques like Kalman filters to mitigate these issues. The proposed ensemble method EM-PSO and hybrid HOP algorithms demonstrate significant improvements in localization accuracy, achieving errors below 2.7 cm and outperforming existing state-of-the-art methods by a 15% variation. The use of RSSI is also explored to reduce power consumption in node positioning. The research concludes that the proposed optimization strategies offer enhanced scalability, localization accuracy, and energy efficiency, making them suitable for various WSN applications.

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CHAPTER-I

INTRODUCTION

Wireless sensor networks (WSN) are widely recognized and commonly used for monitoring and signaling. They have numerous applications, including monitoring, traffic control, weather analysis, and pollution detection. These networks use versatile and easily accessible devices. Important aspects of wireless sensor networks include localization, network deployment, and sensor coverage. Localization is crucial for many applications, as sensor nodes need to know their location to indicate when an event occurs. Finding the sensor is a challenge in localization, and a single method may not be the most effective. With the development of new technologies, several specialized localization methods for sensor networks have been introduced.

1.1 INTRODUCTION TO WIRELESS SENSOR NETWORKS (WSN)

Wireless sensor networks enable the simultaneous monitoring and recording of conditions in multiple locations using specialized transducers (sensors) connected by communication technology. It is common to monitor a wide range of environmental factors, such as air temperature, humidity, pressure, light intensity, vibration and sound levels, power-line voltage, chemical concentrations, pollution levels, and vital physiological processes. Wireless sensor networks are valuable for control and monitoring applications. The sensors utilized in wireless sensor networks are both cost-effective and versatile. Wireless sensor networks have three main features: coverage, deployment, and localization. Localization is crucial due to its central role in numerous applications. Sensor nodes need to know their location to indicate when a specific event occurs. Therefore, sensor localization is critical for many applications of wireless sensor networks. However, locating the node is challenging, and using a single localization method may not be the most effective way to find the position of a mobile sensor.

Several localization methods tailored to sensor networks were developed with the advancement of new technologies.

- The WSN is a network with a large number of nodes.
- Nodes are equipped with embedded processors, sensors, and radios.
- Collaboration among these nodes is utilized for common tasks, such as asset tracking or monitoring of the environment.

1.2 INTRODUCTION TO UWB

Ultra-Wide Band (UWB) is a wireless communication technology that uses radio waves to communicate across short distances, similar to Bluetooth and Wi-Fi. It conforms to IEEE specifications 802.15.4a and 802.15.4z. The Time of Flight (TOF) of a radio signal can be measured with increased precision according to these guidelines. This is especially useful for calculating the position within a few centimeters. With UWB, it becomes possible for the lights to switch on automatically when we enter a room, and for our computer to boot up when we sit down at the desk. UWB brings these capabilities into the real world, where they can have game-changing effects.

- Wireless communication technology using UWB is rapidly advancing as a short-range, high-speed, high-data rate technology.
- It operates over a wide spectrum of frequencies (3.1GHz to 10.6GHz).
- The operation can pass through walls and doors with and without line of sight.
- Multipath fading is highly resistant.
- Low-cost, low-power, all-digital, single-chip architecture.

The imperative for accurate node localization within Ultra-Wideband (UWB) Wireless Sensor Networks (WSNs) stems from the growing demand for precise spatial awareness in a multitude of applications, particularly in environments where traditional localization methods falter. UWB technology, with its high time-domain resolution and low power spectral density, offers a promising solution for achieving this accuracy, especially in indoor and complex settings. This introduction highlights the critical need for robust localization in UWB-based WSNs, driven by applications ranging from navigation and asset tracking to critical military and emergency response scenarios. The ability to precisely pinpoint the location of sensor nodes is paramount for effective data correlation, event detection, and real-time monitoring. Given the inherent challenges of deploying WSNs in diverse and often inhospitable locations, the introduction underscores the importance of developing efficient, secure, and cost-effective localization algorithms that leverage the unique advantages of UWB technology. This is crucial for ensuring the reliability and effectiveness of WSNs in demanding applications where accuracy and resilience are non-negotiable.

1.2.1 Applications of WSN with UWB

Most Wireless Sensor Network (WSN) applications use radio frequency (RF) communication. These applications involve positioning, localization, geo-location, multipath environments, obscured environments, military applications, and low-probability interference rescue applications. For these applications, communication needs to be long-range, high-speed, low-energy, and should not require line of sight between the sender and receiver, with acceptable error rates.

In a sensor node, both a transmitter and a receiver are necessary for actual communication, but they can be further optimized as suggested by ZigBee. WSN systems typically consist of a transceiver unit at each node, allowing wireless communication between nodes. This involves converting a bit stream from a microcontroller to and from radio waves. Recent advancements in wireless communications and electronics have led to the development of low-cost sensor networks. At its core, this project was about meeting the most fundamental need of the application provider (network provider). The application need to enhance the capability in following aspects.

Low cost: All the nodes need to be kept economical because there are a lot of them. Node costs should not be more than one percent of the total product cost.

Small form factor: An antenna and power supply must be small and easily placed in order for sensors to work properly.

Energy consumption: Since most sensors require no power for years on end, low-power detection nodes are suitable. For the wireless sensor network to work as intended, a number of additional requirements must be met. A radio transceiver's operating modes, duty cycle, and models for its energy consumption per bit are among the many elements that must be considered when analyzing its energy consumption behavior. Energy is primarily consumed during the generation of radio frequency (RF) signals. This includes the modulation technique, the goal distance, the transmission power (which is radiated by the antenna), and the electrical components required for RF front ends, amplifiers, filters, etc.

Robustness: Data transmission must remain dependable in spite of interference, localised fading, and shadowing if service quality is to be maintained (e.g., in relation to latency and outage).

1.2.2 OUTDOOR AND INDOOR LOCALIZATION

The variation between range free and range based can be used for outdoor and indoor localization, depending on the application. UWB with WSN implementations can be used in low signaling areas where the node identification is difficult. Location accuracy is a challenging task in these condition the fixed sensor nodes (anchor nodes) allocation is important.

1) **Outdoor Localization:** Many outdoor systems are in use now, such as GPS, LORAN-C, and cellular network radio location. The Global Positioning System (GPS) employs time-of-arrival (TOA) estimates from a minimum of four anchors, in the form of GPS satellites, to resolve a nonlinear four-dimensional issue; however, the agent is not in real-time sync with the anchors. A centralized system, Assisted GPS does most of the calculations, as opposed to individual agents' GPS systems. Centralized, absolute, and non-cooperative localization services based on TDOA are provided by LORAN-C, just like its satellite-based successor. Centralized, absolute, and non-cooperative radio-location services for mobile phones, such as E911, frequently use TDOA.
2) **Indoor Localization:** Wi-Fi, radio-frequency identification (RFID), and ultra-wideband (UWB) localization are examples of currently-available and developing approaches to indoor localization. The RADAR Place Lab and the GSM base stations use centralised, absolute, and non-cooperative methods when they connect through 802.11 access points. Reading radio frequency identification (RFID) tags and readers allows for centralized, relative, and non-cooperative connectivity-based localization. Coarse measurements plague both Wi-Fi and RFID systems, limiting their precision. UWB signals, on the other hand, have certain advantages that make them more suited for interior localization and communication. The high transmission bandwidth of UWB signals makes them well-suited for propagation time estimates due to the fact

that delay estimation techniques become more efficient with increasing bandwidth. Furthermore, multipath components can be handled, and greater signal penetration can be achieved via obstructions, all thanks to the high bandwidth. Thus, it is possible to accomplish accurate range in non-line-of-sight (NLOS) settings and reliable communications in dense multipath environments. UWB signals can detect and perhaps compensate for the impacts of obstacles and NLOS circumstances due to their ability to penetrate them. UWB transmitters are low-cost, simple devices that may be deployed quickly and in large numbers. UWB communication systems are stealthy, energy-efficient, and disruptive to other systems since the power is spread out over a wide frequency range. When it comes to reliable communication and precise range, ultra-wideband (UWB) transmissions are head and shoulders above the competition. In this way, nodes can avoid introducing extra overhead by determining their relative positions using the signals they currently use for communication. Not long ago, when the IEEE 802.15.4a standard concludes, many new systems and applications will be able to be developed in this area.

1.3 LOCALIZATION APPROACHES FOR WIRELESS NETWORKS

This section classifies localization algorithms and describes various signal measures. We apply this categorization to popular location tools, taking both indoor and outdoor settings into consideration.

1.3.1 Measurement Phase

Initially, packets are passed between network nodes (let's say, nodes A and B) close to one another. Receiver (node B) can determine its position with respect to the transmitter (node A) by measuring or approximating one or more signal metrics corresponding to these packets' underlying physical wave forms. These signal metrics are the root cause of localization uncertainty since they are prone to different types of inaccuracy. In this section, we provide a quick overview of typical metrics. We discuss their role in localization, and outline potential sources of mistake.

Nodes can be separated in numerous ways. With the help of the relationship between power loss and distance, we can calculate the RSS. If node B can receive packets from node A, the distance between them is limited to node A's communication range. Estimating the time, it takes for wireless signals to travel from one point to another allows for more accurate distance measurements. This is the foundation for TOA, TDOA, and RTOA. The relative orientations of a node's components can be calculated via AOA estimation when the node has directional or multiple antennas. If you have a linear array with spatial antenna intervals, the time difference between the arrival of any two successive antenna components is determined by the angle AB, which is the impinging signal to the array. Measurements are susceptible to estimation errors. Examples of factors that can lead to substantial inaccuracies in RSS estimators include shadowing and multipath. Location data produced by the connection metric is sometimes coarse when the communication range is large or the network's connectivity is low. Errors can occur in signal measurements that rely on the time delay between the transmitter and the receiver, such as TOA, TDOA, RTOA, and AOA. Because of these impediments, the distance estimate may be inclined upwards, a phenomenon known as non-line-of-sight (NLOS) situations. There are a number of potential sources of mistake in calculating arrival timings, including noise, interference, multipath, clock drifts, and others.

1.4 UWB LOCALIZATION: Fundamentals, challenges and framework

Localization is an essential aspect of wireless sensor networks (WSNs), and researchers have taken a keen interest in this area. Miniature, low-power, low-cost, and ad hoc communication sensors make up a wireless sensor network. In wireless sensor networks, localization or positioning involves determining the physical location of sensor nodes, which is crucial to estimating the point of origin of events in communication networks. Various localization methods are used in different applications due to the different positioning accuracy requirements, and some special scenarios, such as forest fire detection, present several challenges. Our focus is on different localization-based applications, which require estimating the location information, and different measurement techniques and strategies for range based and range free localization. Finally, the complexities, cost, and scalability of the method are discussed in detail. This section provides a brief overview of some of the more common methods used for localization and tracking in UWB sensor networks. The main causes of estimation mistakes and factors connected to positions will be examined later on. Traditional range-free localization algorithms and protocols in WSNs are incompatible with most applications that require unique solutions due to harsh surroundings and channel characteristics.

1.4.1 Localization in UWB Sensor Networks

Transmitting ultra-wideband signals using nanosecond or nanosecond signals enables the ultra-wideband signal to consume less energy, have compact network systems, and have higher location precision and high resolution. Consequently, trustworthy and accurate indoor real-time location is a perfect fit for UWB technology. Unfortunately, there are still some accuracy issues with UWB, especially when it comes to 3D indoor localization, despite its convenience. To overcome this obstacle, hardware placement or ranking algorithms need be enhanced. Many obstacles, including as shadowing effects and multipath fading, remain to be conquered.

The stand point of UWB localization methods encompasses a variety of techniques, each with its own set of advantages and limitations. Time-based methods like TOA, TDOA, and TW-TOF offer high accuracy, particularly in line-of-sight conditions, but require precise time synchronization. Angle-based methods, such as AOA, are less accurate but can be useful in specific scenarios. Hybrid approaches aim to combine the strengths of these methods, while range-based methods utilizing RSSI provide a lower-cost and less complex alternative, albeit with reduced accuracy. Ongoing research is focused on addressing challenges like multipath propagation, non-line-of-sight conditions, and computational complexity, with a trend towards incorporating machine learning and developing energy-efficient solutions to enhance UWB localization for diverse WSN applications.

1.4.2 Conventional two-step UWB localization

The two-step positioning is a common technique used by most localization systems in distributed sensor networks; it consists of two stages parameter extraction and data fusion. Figure 1.2 provides a high-level overview of the standard two-stage UWB localization process.

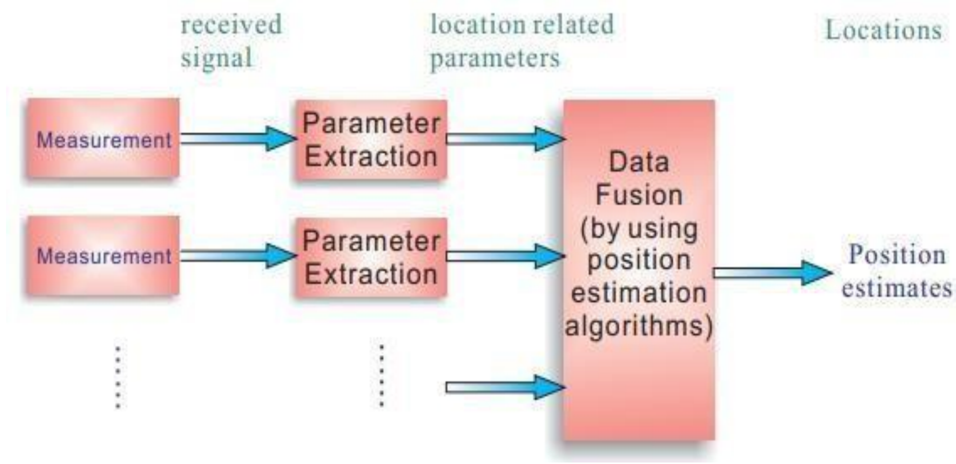


Figure 1.1: Illustration of the conventional two-stage UWB localization process.

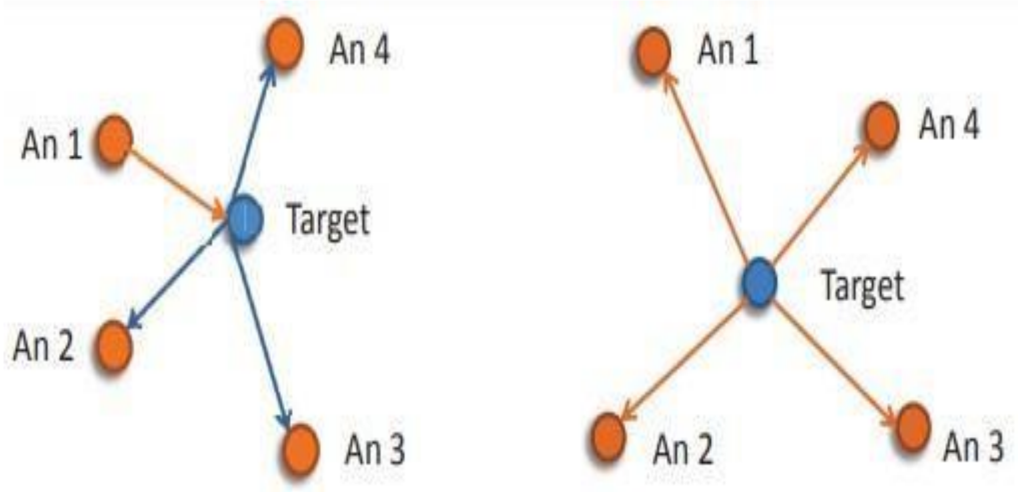


Figure 1.2: Active and Passive localization. Here is an example of passive localization and one of active localization.

Anchor nodes are denoted by red dots, while the node requiring localization is shown in blue. The target node in the passive localization example shown on the left is not equipped with any sort of transmitter or receiver, and instead merely acts as a mirror to reflect incoming signals. The target node has transmitter equipment and sends signals to the anchor nodes in the right figure, which is an example of active localization.

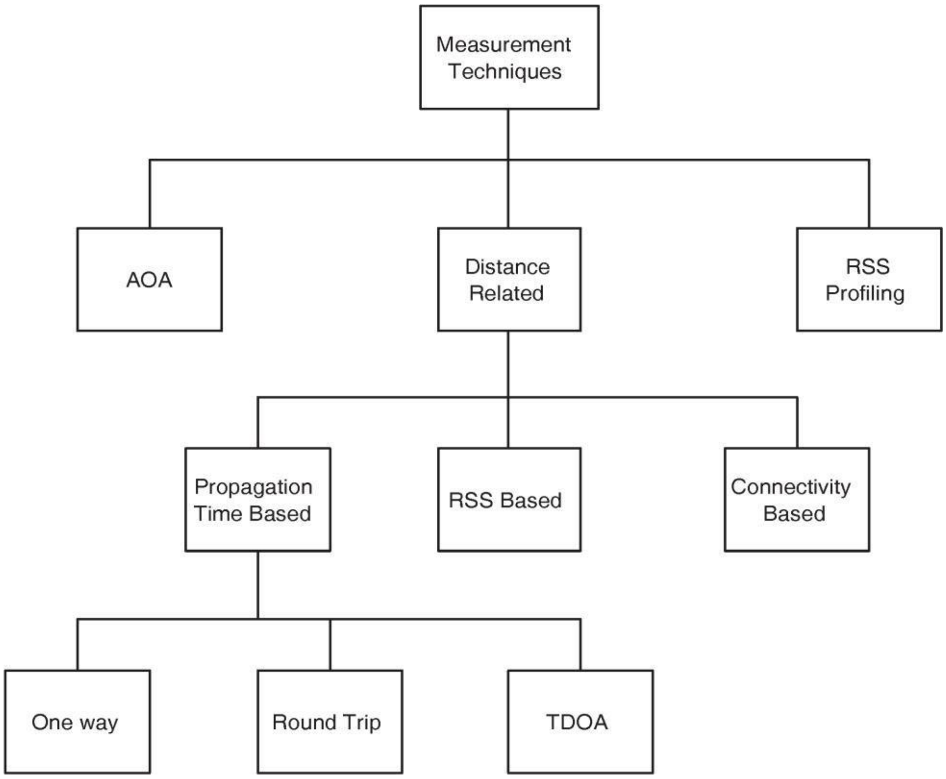


Figure 1.3: Mobile node estimation

To begin, radio waves are used by UWB sensor networks to take a reading, and then the CIRs between the anchor nodes and the target nodes can be determined. Following that, several characteristics of the signals, such as their amplitudes, phases, and delays, are retrieved. An estimate of the range (TOA or time delay) is made in a range-based localization system, while in a range-free localization system, an estimate of the angle (AOA) or power (RSS) is made. The retrieved parameters are then used to forecast the target node's location using appropriate signal processing methods. The range estimation step and the location estimation step are what need to be taken to implement the range-based localization system. By first estimating the time of arrival (TOA) or time difference (TDOA) of signals propagating between the target node and the reference sensor nodes, we can then multiply these values by the speed of light to get our distance parameters (range or range difference estimates). The term "range estimation" describes this process. After that, accurate location estimation algorithms are used to infer where the target node is based on the estimated ranges.

It is clear from this that the channel parameter and the physical separation of the two nodes are the only two inputs necessary to calculate an accurate lower bound for the RSS estimates. To put it another way, even if UWB bandwidth

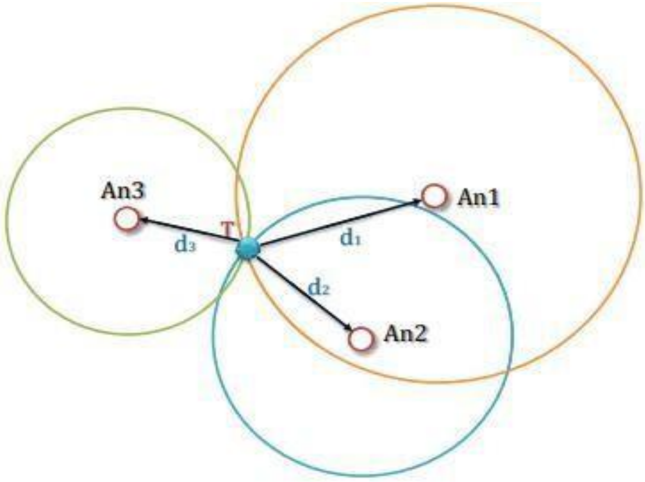


Figure 1.4: A 2D range-based localization example where d1, d2, and d3 are the estimated distances between the target node and the three anchor nodes.

Further, as distance between nodes grows, RSS measurement accuracy decreases. RSS localization is straightforward and needs less precise clocks and less temporal synchronization between nodes than other methods. However, the high resolution provided by UWB cannot be utilized by RSS, and vice versa. Fading causes it to be incorrect in high-scatter settings. Fading has a a dynamic state to distance because of propagation effects (such as physical phenomenon, reflection, shadowing, and multi-path). Furthermore, it is sensitive to the transmission inconsistency and non-stationary parameters and requires a particular channel behavioral mode. The fading due to path loss as a function of distance can be described mathematically; thus, a path-loss model is required; however, the path loss exponent may be unknown in advance.

1.4.3 Time Difference of Arrival (TDOA)

TOA is tough because receiver-transmitter synchronization is required. Another range-based technique is TDOA. If the anchor nodes are synchronised, TDOA measurements can be taken even if the target node and anchor nodes are not. TDOA is measured similarly TOA.

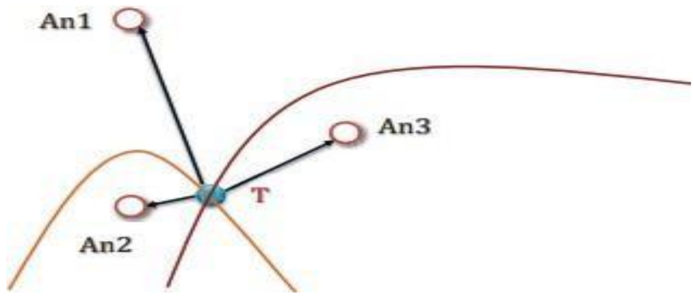


Figure 1.5: A simple illustration of the TDOA-based hyperbola localization technique in a 2D space.

The period of time between two signals leaving two anchor nodes and reaching the destination node. This method is commonly employed in RTLS because to its rapidity and accuracy. When it comes to localization, TDOA-based systems aren't dependent on absolute distance estimates between Tx-Rx pairs, as illustrated in Figure. Typically, anchor nodes maintain a consistent synchronisation. When working in two dimensions, determining the location of the target node requires a minimum of three anchor nodes and two time-domain-of-arrival (TDOA) observations. Every time difference between two points (TDOA) can be represented as the centre of a hyperbola, with the points surrounding it spaced at regular intervals (time differences). The end product is a system of hyperbolic coordinates where the target node is positioned between the two anchor nodes. For example, one way to determine TDOA is to estimate TOA at both anchor nodes and then subtract one from the other. With this scenario, we'll pretend that two separate anchor nodes have time delay estimates of 1 and 2, respectively. Without synchronisation between the target and anchor nodes, the TOA estimates at the anchor nodes need to take into consideration both flight time and temporal offset. Given that the anchor nodes are in perfect sync, the time offset for each TOA estimate is uniform. Based on this, we can determine the TDOA.

$\hat{r}$TDOA = $\hat{r}1 - \hat{r}2$

One alternative is to measure TDOA by correlating the signals received by two anchor nodes; this involves taking the time it takes for one node's signal to be received and then finding the delay that corresponds to the value with the highest cross-correlation. Deterioration in the performance of cross-correlation-based TDOA estimation may occur over multipath channels.in a dramatic approach. A generalized cross-correlation (GCC) strategy is suggested to improve cross-correlation performance.

1.4.4 Optimization of Location with localization algorithms improvements in UWB

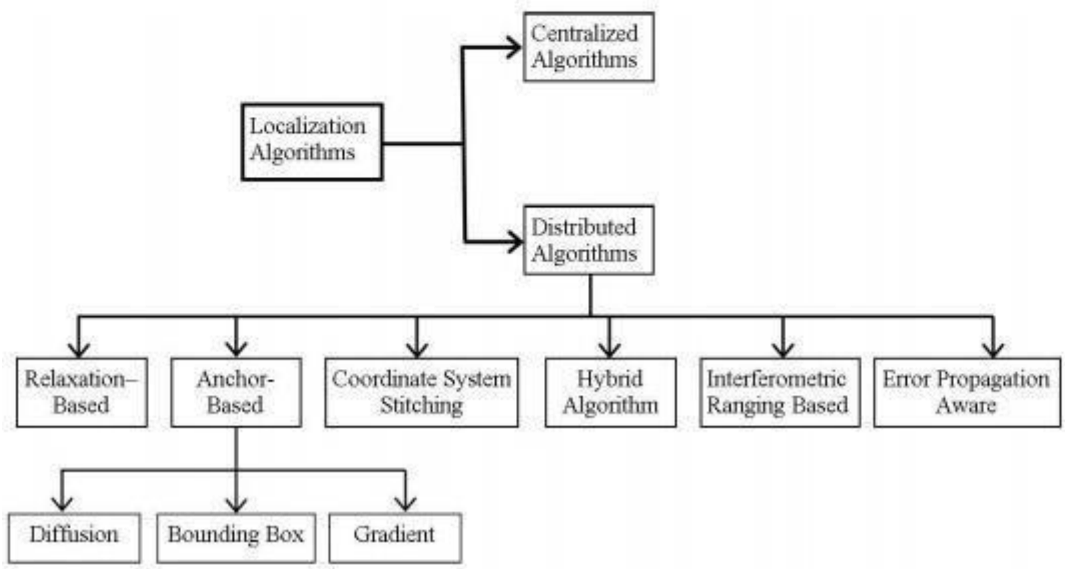


Figure 1.6: Localization Algorithms Classification

The utilization of wireless sensor networks (WSNs) in a range of applications. In their study, the use of hybrid algorithms for anchor-based node localization in UWB indoor networks is investigated. This technology has been created by several different researchers. It has become increasingly popular to use GPS and maps to locate a person in recent years. Buildings are a barrier to GPS location signals that becomes GPS unable to function indoors. A number of indoor localization methods have been created as a result of GPS location inaccuracies. These include infrared, Wi-Fi, Bluetooth and Zing Bee techniques as well as radio frequency (RFID)/Ultra-Wide Band technology. The use of UWB technology increases the durability.

PSO is a well-known optimization method that is based on conventional instinctive networks, that is why it has become so successful. An entire swarm of particles flies and searches in a limited area at a given pace, attempting to locate the ideal location in pattern. Simple implementation and high performance have made PSO a popular tool for solving real-time scheduling and engineering challenges. Although most UWB indoor localization systems use only one PSO algorithm, our technique attempts a better solution by integrating multiple PSO algorithms. As a result of our observations, we believe that it is difficult to attain flawless performance using present communication techniques alone. In conventional UWB localization methods, the system controller uses various localization techniques to estimate the present positions of the users. The accuracy of conventional approaches is dependent on the type of localization algorithm and controller configuration. The indoor positioning accuracy of UWB localization was improved in this work by introducing hybrid algorithms to optimize after TDOA measurements were used.

There is a wide gap between the measured and actual targets due to the limitations of hard equipment and environmental obstacles. This study aims to bridge the gap by enhancing in phases following a communication measure. The distance between the beacon and the target nodes is currently assumed utilizing TDOA parameters in the localization process. Further, target nodes' 2D and 3D coordinates are calculated using an improved Chan algorithm. After that, the estimated position of target nodes is optimized using ELPSO, BPNN.

1.5 BACKGROUND OF THE STUDY-

In a wireless sensor network, many dispersed devices that contain sensors work together. It was originally intended for use in military settings that the wireless sensor network would be developed. Despite this, there are a growing number of uses for wireless sensor networks. Their popularity is growing, and with it, the number of scholars interested in them. In various fields of electronics, new developments and modifications, consumer electronics, and sensor technologies with short- and long-range connection are gaining significant importance. Application areas for wireless sensor networks are vast and varied, spanning various fields such as computing, communications, healthcare, defence, and military operations, among many more. With more sensor nodes in the network, wireless sensor networks become more important. A majority of WSNs rely on sensor self-positioning, which in turn requires knowledge of the network's location.

The sensor plays a significant role in the field of wireless sensor networks. The sensor is an instrument that takes readings of some physical property and transforms them into electrical impulses. It is impossible for a sensor network to function without sensors. Thanks to these developments in sensor technology, wireless sensor networks have been introduced. Finding the exact geometric location of a sensor node inside a network is known as localization. With respect to the reference location, this location is approximated. Constraints such as size, cost, and power improve the localization algorithms to tackle emerging problems. When the precise whereabouts of some stationary or mobile equipment are unknown, localization becomes crucial. When thousands of sensors are dropped from an aeroplane in order to monitor humidity and temperature in fields and woods, for instance, the operator has very limited control over the exact placement of each node.

1.6 MOTIVATION

WSN has several limitations, including size, energy consumption, and cost. Prior to developing any localization method, it is essential to take these limitations into account. Data transmission and communication between nodes uses a lot of power. There are a lot of localization algorithms out there, but most of them are specific to certain applications. An application-specific localization technique may not be well-suited for other WSN applications. Similarly, static sensors aren't suitable fit for certain localization techniques designed for mobile sensor nodes.

Localization of sensor nodes can be a problem, which is why researchers are dealing with a number of issues. Localization in WSNs is an exciting field with a lot of potential for new researchers. Designers of localization algorithms should keep low power consumption, hardware costs, and algorithm deployment in mind while making these designs. The use of global positioning systems (GPS) for sensor node localization is inappropriate due to its high cost, low energy efficiency, huge hardware requirements, and line-of-sight issue. Every node would have to have a GPS antenna, which would make the network larger and more expensive to establish. In addition, GPS is not a good fit for a network such as a WSN because of the amount of energy it requires. Designs for WSN localization systems are more difficult than those for other types of networks. Think about all the constraints, such battery life, computing power, memory, data speeds, and size, just like with WSNs. Localization systems might lead to unexpected handling mistakes due to line of sight (LOS). Without accuracy, no localization method can be considered practical. The accuracy of localization is reduced when the position of the node is underestimated. Accuracy in localization suffers when individual nodes in the network provide inaccurate coordinates during self-localization, which lowers network accuracy. When designing a localization algorithm, node density is crucial. Ideally, for beacon-based algorithms to achieve precise localization, the density of beacons should be high. However, there is no guarantee that beacons will actually achieve localization reduces precision, rendering localization techniques ineffective. Nodes in movable WSNs are allowed to leave and relocate as needed. Topological changes could happen in that situation. In order for mobile WSNs to adapt to changes in topology, a scalable method is required. In addition, the position of a node that is inherently movable is notoriously difficult to predict repeatedly. Nodes that are mobile are always moving. The localization technique should be accurate with a smaller number of beacon nodes, but as the number of nodes increases, the accuracy of localization improves and becomes more precise. Deploying localization in actual 3D space should be accessible.

Versatile localization techniques can provide flexibility and adaptability across various applications. They can optimize resource usage and ensure efficient communication between nodes, regardless of the specific conditions or requirements of different WSN deployments. This adaptability can lead to more sustainable and cost-effective solutions in the long run. The concept of versatile localization techniques, particularly within the context of Ultra-Wideband (UWB) technology, is crucial for realizing the full potential of Wireless Sensor Networks (WSNs) across a diverse range of applications. UWB's inherent characteristics, such as high time-domain resolution and immunity to multipath interference, make it a strong candidate for precise localization. However, the varying demands of applications—from indoor asset tracking to outdoor environmental monitoring—necessitate adaptable solutions. Versatile UWB localization techniques would encompass a suite of methods, including time-based (TOA, TDOA, TW-TOF), angle-based (AOA), and potentially hybrid approaches, allowing for dynamic selection or combination based on the specific deployment scenario. For instance, in environments with dense obstacles and non-line-of-sight (NLOS) conditions, hybrid methods or robust algorithms incorporating machine learning could be employed to mitigate errors. In contrast, simpler applications with clear line-of-sight might leverage less complex, energy-efficient techniques. This adaptability extends to resource management. By dynamically adjusting localization parameters, such as transmission power or sampling frequency, based on application requirements, energy consumption can be optimized, prolonging the lifespan of battery-powered sensor nodes. Furthermore, versatile techniques can facilitate seamless communication between nodes, enabling efficient data aggregation and dissemination, even in dynamic or heterogeneous WSN deployments. The long-term benefits of versatile UWB localization include increased sustainability and cost-effectiveness. By avoiding the need for specialized hardware or inflexible localization solutions, WSN deployments can be scaled and adapted to evolving needs without incurring significant costs. This approach also promotes interoperability, enabling seamless integration with existing UWB systems and facilitating the development of innovative applications across various sectors. Ultimately, versatile UWB localization techniques are essential for unlocking the full potential of WSNs, enabling them to operate efficiently and reliably in diverse and challenging environments.

1.7 OBJECTIVES:

In this work, our major focus is on achieving high node location accuracy with a very small number of anchor nodes in dynamic (anchor and target nodes may have some mobility) and static scenarios by applying heuristic-based algorithms. The objectives are framed as follows

- Design a range-based error control model using UWB to estimate optimal node location in Homogeneous dynamic WSN with various soft computing approaches.
- Design a range free error control model using UWB for estimation of optimal node location in Homogeneous dynamic WSN with various soft computing approaches
- To build up and appraise a stochastic algorithm for calculating the optimized position of the target nodes with lower calculation loads and with high positioning accuracy
- Comparative analysis of existing Techniques with the developed Techniques at different stages for validation of the proposed algorithm.

1.8 CONTRIBUTION OF WORK

The present work focused on accurate measurement of beacons (mobile nodes) with 4 anchor nodes. Two measurement methods of least square and tetrahedron taken in NLOS environment for indoor localization.

2D method of measurement; Least squares used to estimate the node localization with TDOA to calculate distances from various sensor nodes (anchor nodes). An improved Chan algorithm used in measuring distance an average of 3 measurements for different anchors were estimated.

3D method of measurement: Tetrahedron based 3D measurement adopted with varying (x,y,z) measurement position from multiple anchors to evaluate accuracy by means. Target beacons distance average optimized with improved Chan algorithm using Kalman filter to avoid noise disturbances.

Range based localization: Measured 50 mobile nodes (beacons) in an indoor area of 100 square meters range with 2D and 3D. An improved PSO implementation done with two methods of **Ensembled Learning (EL-PSO)** and **Back propagation Neural network (BPNN-PSO)** techniques to minimize measurement error.

Dv-Hop, with the least square method, divides the location technique into three stages. In the first and second phases, the predicted distances from reference nodes O(x,y) to beacons A1 (x1,y1) then it is measured with h(hop distance between different beacons). The work was further measured with the centroid method with respective time of reaching the value.

A 3D method of measurement adopted with centroid to calculate average HOP to fix the mobility of node and measurement from different anchors. An area of 20MtsX 20Mts with max free range of 100Mts taken in to consideration.

Range free localization updated with sequential DV-HOP and the algorithm improved with centroid measurement. 30 nodes taken in dynamic mode with 4 anchor nodes in place. The measured error has been optimized by using improved PSO algorithm further improved with **Ensemble Multi node** method to reduce the error.

Hybrid algorithms used in the present research combine the strengths for both range-based and range-free localization methods, which makes them more reliable and accurate. They take advantage of the strengths of both methods, such as the accuracy of range-based methods and the robustness of range-free methods**.** These algorithms will provide more accurate localization results than traditional range free methods. Furthermore, they are computationally efficient, making them suitable for real-world applications. Hybrid localization algorithms combine two or more methods, such as GPS and inertial navigation, to improve the accuracy of localization. This can help to reduce errors due to GPS drift and multipath effects. Hybrid algorithms can also be used to reduce the number of sensors required in a system.

1.9 THESIS ORGANIZATION

Chapter-1: gives a brief information about the wireless sensor networks with UWB applications, challenges in UWB for target node localization. This chapter also discussed about the, measurement techniques, optimal techniques, background of the study, motivation, objectives, contribution of work used in the present work.

Chapter-2: A detailed literature survey about measurement techniques, UWB implementation, optimization algorithms and recent methods of error localization.

This chapter also reviewed the PSO algorithm implementation in range- based and range free environments and hybrid techniques of improving PSO.

Chapter-3: This chapter presents about range-based localization with novel methods of error localization. In the present day, localization depends on TDOA characteristics to infer the distance between the beacon and the target nodes. As an added step, we use an enhanced Chan algorithm to determine the 2D and 3D coordinates of the target nodes. The next step is to optimize the estimated positions of the target nodes using ELPSO and BPNN. For high computational accuracy in node localization, a hybrid mixes of Ensemble learning and Back propagation with PSO is recommended. From the initial four positions of the target node, precise measurements have been taken, including the maximum and minimum localization errors as well as the average localization.

Chapter-4: This chapter presents about range free localization with DV-Hop for location accuracy. Improvement methods of DV-Hop considered in the present work as CC- DV-Hop and Hybrid DV-Hop considered for the variation in localization and a new method An online sequential DV-Hop method is proposed.

Chapter-5 An online sequential DV-Hop method is proposed for localization of nodes. Further research continued with optimization of error localization using improved PSO and ensemble method of PSO as proposed optimal technique. The results compared with the localization optimal results of BBO and FA

Chapter-6: This chapter presents the comparison of results in the two-methods range based and range free methods with the existing results.

Chapter-7: Conclusions and future recommendations

CHAPTER-II

LITERATURE REVIEW

A wide variety of uses exist in short-range networks for wireless device position estimation. In order to make these uses a reality, wireless systems can make use of ultra-wide band (UWB) transmissions, which offer precise locating capabilities. According to Zafer Sahinoglu (2008), Ultra-Wideband Positioning Systems exist. Unmanned Wideband (UWB) transmission technique is appealing for short to medium distance localization, especially in places where GPS is not available: Achieving centimeter-level distance resolution is made possible by resolving sub millisecond delays, while broad transmission bandwidths enable robust communication in dense multi-path environments. In order to determine where the proposed systems could be lacking in research, a comprehensive literature review was done. There is a wide variety of methods for implementing localization techniques, and researchers have created a number of algorithms to enhance the efficiency and accuracy of localization. It is possible to classify localization methods into two categories. Range-based and range-free localization techniques. Received Signal Strength Indicator (RSSI) is a range-based localization technique. [**Barsocchi et al.** (2009); **Cheng et al.** (2011)], Time of Arrival (ToA) [**Chan et al.** (2006); **Xu et al.** (2011)], Time Difffference of Arrival (TDoA) [**Gillette and Silverman** (2008)] and Angle of Arrival (AoA) [**Kułakowski et al.** (2010); **Rong and Sichitiu**(2006)]. Node localization methods that rely on range information (such as angle or distance) to determine the node's position incur higher hardware costs than range-free methods, but they provide more accurate results. Distance Vector Hop (DV-Hop) and Centroid Algorithm were published by Deng et al. (2008). [**Chen et al.** (2010)], Approximate Point in Triangle (APIT) [**zeng Wang and Jin** (2009)] and Multi-Dimensional Scaling (MDS) [**Shang and Ruml** (2004)] are some of the range free techniques.

2.1 Related- Research Work

Mobile node localization become essential in crucial areas like environmental monitoring, target tracking, and shadow areas are just a few of the many use cases that are seeing widespread adoption of small, cheap sensors with minimal energy consumption and limited computer resources. Node localization is often a required part of the system parameters in these applications. Mostly node localization divided in to two stages, one is measurement stage and other computational stage.

2.1.1 Measurement stage

There are three general categories of measurement techniques for WSN localization [Mao etal. 2009]. Measuring the Angle of Arrival (AOA), measuring the distance from the antenna with respect to time, and profiling the Radio Signal Strength (RSS).

1. Received Signal Strength (RSS)
2. Time of Arrival (ToA)
3. Time Difference of Arrival (TDoA)
4. Angle of Arrival (AoA)
5. Network Connectivity based/ Proximity
6. Scene/Picture Analysis

1. RSS: Measuring the received signal strength allows one to approximate the distance between two sensor nodes. Most sensors are capable of measuring RSS. The distance from the RSS is estimated using a monotonically decreasing function. The localization algorithms utilize this distance to ascertain the location of the sensor nodes. The first is that it is very difficult to estimate distance using RSS in wireless environments, particularly those that are both indoors and outdoors, and which contain irregular objects within the measuring region. In addition, it can be difficult to identify the model parameter.

2. ToA: The range-based time of arrival (TOA) method offers the most precise localization in UWB sensor networks because of the strong temporal resolution (big bandwidth) of UWB signals. The majority of TOA-based systems typically accomplish localization by estimating both range and position, also known as TOA estimation [S.Gegici et al. 2009]. Due to the need for precise synchronization of the transmitter and receiver clocks, the ToA based technology adds complexity and expense to the ranging process.

3. TDoA: The utilization of transmission media with varying speeds is important to TDoA. According to Karl and Willig (2007), one way to determine the distance is by

comparing the arrival times of these signals. Assuming both receivers are in sync and known whereabouts, the time difference of arrival measurement finds the relative delays in the arrival times of a transmitted signal at each receiver. In order to determine the exact position of the transmitter using this method, three receivers are required. Both multi-path and synchronization errors impact accuracy.

Raising the separation between receivers improves accuracy by extending the gap between their arrival times.

4. AoA :In order to determine AOA, one can use the amplitude of the received signal or one can use the phase of the antenna. From these methods, we may determine the angle between the anchor node and the unknown sensor node. That is why the area around the mystery sensor is a line whose angle is defined by the anchor node. In AOA measurement approaches, it is necessary to use a minimum of two anchor nodes in order to determine the position of an anchor node. The localization mistake could be considerable even if the measurement error is limited. The direction characteristics of the antenna have an impact on measurement accuracy, which is already complicated by factors like shadowing and multipath effects in the measuring environment. Severe inaccuracies in measurement precision can occur when a multipath component is introduced into the transmitted signal, making it seem as though it originated from an alternate direction [50]. The AOA method is not very useful for localization unless massive antenna arrays are used. For WSNs using small sensor nodes, this means it is totally inefficient in terms of energy consumption.

5. **Proximity:** Given that measuring distance requires nothing more than communication between sensor nodes, this is the most straightforward approach. Nodes outside of a sensor node's transmission range will not be measured. For this method to work, no supplementary gear is needed. [**Torre and Rallet**(2005)].

6. **Scene/Picture Analysis:** The methods of RSS, ToA, TDoA, and AoA are very different from picture analysis. Scene or picture analysis forms the basis for measurement in picture analysis. One drawback of this strategy is the additional complexity and hardware requirements it requires.

7. Computational stage Triangulation

itis based on the geometric connection between anchor nodes and unknown nodes. The unknown node's location is determined by observing the angle at which signals arrive from the anchor nodes. Next, a statistical method is used to reduce the estimate error. One such method is the maximum likelihood algorithm.

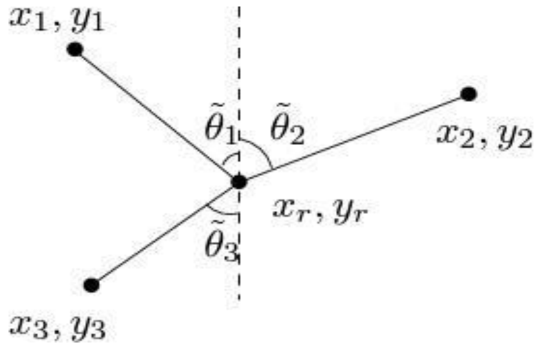


Figure 2.1 Measurements for the triangulation scheme.

The trilateration method determines the location of a node by comparing its measured distance to that of other known anchor nodes. Clearly, this node needs to be placed in the circle whose radius is equal to the distance between the set of nodes, with the anchor node serving as its Centre. This can be seen in the figure for any given distance. 2.2.

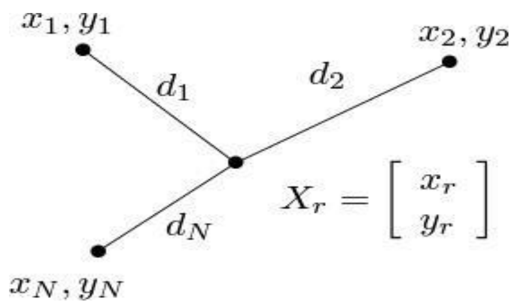
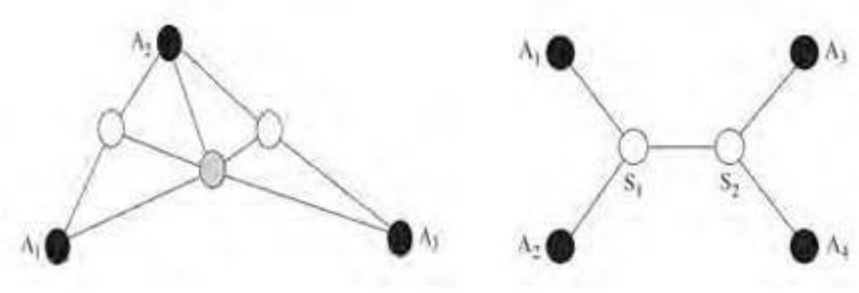


Figure 2.2 Trilateration scheme.

Multilateration: A minimum of three anchor nodes are required for iterative and collaborative multilateration in order to pinpoint the location of the fourth unknown node. If there aren't three nearby anchor nodes, expanded multilateration methods can nevertheless estimate position. After determining on a position, nodes can start broadcasting messages that serve as anchors. Locating individual nodes in a network is a continuous process.



a) Iterative b) Collaborative

Figure 2.3 Multi Trilateration scheme.

2.1.2 Classification of localization algorithms

1) Centralized and Distributed Algorithms
2) Range free and Range based Algorithms
3) Anchor free and Anchor based Algorithms

Centralized and Distributed Algorithms: When using a central server for computation, centralized algorithms are the way to go. The computing limits of nodes are resolved by centralized algorithms. According to K. Langendoen and N. Reijers (2010), communication with BS is more energy-intensive than computation in these algorithms. The sensor nodes are used to do computation in distributed algorithms. The energy consumption of these algorithms is lower than that of Centralized algorithms since they rely solely on inter-node communication.

Range free and Range based Algorithms: Algorithms that do not require a range of values incorporate neighborhood and hop counting methods. Although the results are not very exact, these methods are cost-effective since they only require connectivity information to pinpoint the position of nodes. Some range-based methods are RSSI, TDoA, and AoA. Although these methods necessitate supplementary hardware for TDoA and AoA, they significantly improve localization accuracy. Radio or microphone arrays for AoA, and an acoustic or ultrasonic module for TDoA. Since each node in AoA contains a speaker and many microphones, the hardware required for AoA is more costly than that required for TDoA.

Anchor free and Anchor based Algorithms: Anchor nodes are nodes that are known to have precise location coordinates, either by GPS or by being manually introduced. To acquire global coordinates, we can employ anchor nodes. However, GPS devices are prohibitively expensive and cannot be used for indoor localization due to their reliance on Line of Sight communication [Y.Liu et al., 2010]. When deploying 10,000 nodes with 500 beacons, for example, or when deploying nodes from an aircraft, it would be extremely impractical, if not impossible, to use pre-programmed nodes with their locations as an alternative to GPS. Depending on the situation, we can either employ anchor-based nodes that are manually placed to know their coordinates or utilise anchor-free nodes that readily obtain relative coordinates for indoor localization.

2.2 LOCALIZATION OF NODES IN WIRELESS SENSOR NETWORKS

To enhance the accuracy of indoor localization and optimise the allocation of node resources in wireless sensor networks (WSNs), an equal-arc trilateral localization algorithm based on received signal strength indicator (RSSI) is suggested. This algorithm would improve measurement accuracy and beacon node layout. By modelling the beacon nodes in an equal arc triangle arrangement, they ensure that unknown nodes' motion tracks are consistently within an acceptable communication distance, leading to more accurate measurements. **Wei Wang et al (2019).**Statistical based optimum node localization was proposed as a means to ascertain the locations of nodes in WSNs. To get a better estimate of the channel path-loss, this method takes into account the features of WSN additive noise. Another important finding is the lower bound of the non-convex function, which greatly simplifies the problem. **Souparnika Jadhav et al (2022)**.While range-based localization has received greater attention, range-free localization makes advantage of a wide variety of measuring procedures and approaches. They continue by looking at a plethora of localization-based apps, all of which stress the importance of precise location estimation. Data tagging, target monitoring, and location-based applications are just a few of the many uses for localization that WSNs depend on (Anup Kumar Paul et al., 2017). Consideration of numerous subtopics, including 3D and mobile anchor-based localization algorithms, is essential for developing protocols for WSNs, and the same is true for localization. Recent studies have focused on a few well-liked approaches that make use of static 3D networks. The authors of the study are Putri Kevin and colleagues (2019). The phenomenon known as Non-Line-Of-Sight (NLOS) error occurs when a signal encounters physical obstacles that distort its path. It has been used to approximate a convex optimisation problem for the node localization problem in WSN in non-line-of-sight (NLOS) settings. Researchers in the study propose a method for NLOS localization that relies on residual analysis to mitigate the impact of NLOS inaccuracy. A model dependent on the time of arrival (TOA) is used to compute the distance. Based on research conducted by Yan Wang and colleagues in 2018. A Study on the Efficiency of Wireless Sensor Network Positioning. In order to compare their performance, standard DV-based positioning methods and proximity-based locating methods are in use. In order to find the best approach for the situations being studied, the researchers will examine how many aspects impact the accuracy of localization approaches. A study conducted by Peter Brida1 and colleagues in 2011. From the perspective of networked self-localization, Kai Xing Min Ding et al. (2005) examined the connection between WSNs. The system has been modelled as an ad hoc graph. In addition, the authors determined the probability of finding a specific unknown node using an analytical equation that depends on density. Researchers have also looked into the issues using simulated case studies. Wireless sensor networks (WSNs) have recently garnered a lot of attention from the scientific community. WSN localization relies on range-based and range-free techniques.**Asma Mesmoudi1 et al (2013).**Nodes in a WSN need to know where they are before they can send or receive data, which is necessary for wireless applications. Every node provides its own coordinates on the 3D measured node localization during the localization procedure. Data collected by sensors in a wireless sensor network (WSN) is meaningless without knowing the precise location of the occurrence, so the position of the target node is crucial. Reason being, most WSN applications rely heavily on knowing where the sensor nodes are located. A PSO-based computational intelligence method for optimal distributed localization of randomly moving target nodes is proposed in this research. The space under observation is encircled by a system of anchor nodes. Researchers Parulpreet Singh and associates (2017). A 3D MWSN node localization method that accommodates the unknown and anchor nodes' stochastic mobility using a hybrid adaptive MCB-PSO approach. An improved particle swarm optimization (PSO) approach to locating roaming nodes is presented as Monte Carlo localization boxed (MCB). This solves the problem of particle degeneracy that plagues traditional MCB. To describe the unpredictable movement of anchor and unknown nodes across multiple time scales, the approach suggested uses a random waypoint model **Hua Wu, et al (2020).**

2.3 LOCALIZATION IN UWB SENSOR NETWORKS

Advancements in areas like wireless communications and micro components based on MEMS (Micro-electromechanical systems) technologies have helped fuel the growth and development of WSN. The research involved deploying three different UWB-based range methods on Decca WI No nodes.**Salick Diagne1et al (2018).** RFID-based solutions are the only widely distributed items for paying attention when monitoring with WSN deployment. Radio-frequency identification (RFID) technology is an example of a implementation of WSN**Navneet Kaur et al (2022).** Cooperative localization methods are used in UWB wireless networks. Short- to medium-range localization is best accomplished with ultra-wideband transmission technologies. **Henk Wymeersch et al (2009).** A system-level description of the development of a three-tier Ultra-wide Band (UWB)-based indoor localization system. Tags are self-sufficiently powered and built using only UWB transmitters for communication, making them cheap, compact, and ultra-low in power consumption. In order to make the system more cost-effective, hubs are used as intermediary relay stations between transmit-only tags and base stations.**Zheng Li, (2009).Bin Li,** To reduce cross-network interference, researchers recommend looking into cognitive- based dynamic spectrum accessing schemes, in which Ultra-wide Band (UWB) sensors take advantage of unused spectrum by monitoring the local spectral environment**Zheng Zhou,Weixia et al (2010)**. **Diwu et al (2011)** emphasized that localization serves numerous useful purposes in WSNs. Acoustic, infrared, and ultra-wide band (UWB) media are among the technologies that have been utilised for localization. A bottom-up, unified design of a communication architecture based on UWB and associated protocols for localization in WSNs is the goal of their research. a novel UWB indoor GPS-like local positioning system that can monitor an unlimited number of assets with no detriment to the measurement update rate. Mathematical modeling and uncertainty sources are studied to improve the system's precision **Luca Santoro et al (2021). Leyla Nosrati et al (2022)**said that using ultra-wideband (UWB) technology for precise indoor localization has garnered interest for a long time. Following the pre-processing of the received signals, two novel approaches are presented to reduce the range error caused by multipath components. Start with the time and power matrices derived from the A pair of machine learning algorithms—multi-layer perceptron (MLP) and support vector machine (SVM)—are fed the received UWB signals. Other parameters, which have been neglected in other studies, are also taken into account in this one, in addition to algorithms for distance estimation and position calculation. Among these considerations are the following: movement, functional construction, linked data transfer, latency in position updates, and the need to track several terminals. **Juan Chóliz et al (2011).** An efficient multipath 3D node localization algorithm for ultra-wide band (UWB) wireless sensor networks It combines 3D Chan/Taylor position estimation with multipath delay estimation using the Modulation-Propagation Model (MPM). Our method is significantly more computationally efficient than previous range-based approaches, while also improving robustness and localization accuracy in a noisy, multipath environment. The suggested approach can be used for 3D node localization in its speed, accuracy**Hong Jiang, et al (2014).** The unknown node's precise location is calculated by averaging the coordinates of anchor nodes whose positions are known. Using weights, the proposed method can be refined to pinpoint the original position of the removed node **Zhao et al. (2013)**.Numerous anchor nodes are needed to determine a node's location using the Received Signal Strength Indicator, therefore it's clear why node localisation is so useful in a wireless sensor network. In this research, they propose using a genetic algorithm for wireless sensor network localization to improve positioning accuracy with a less number of anchor nodes**Kapil Uraiya et al (2014).**An anchor node's location can be determined by a reach centroid localization algorithm that employs a validation process. Using the strength of the signal received, a verification is made. Using the received signal intensity, the node's vicinity or real position can be calculated **Adeniran Ademuwagun et al. (2017).**

2.4 Detailed Review on target node Localization 2D

Parulpreet Singh et al (2017) Optimisation for location error is performed using a PSO-based algorithm. Numerous military and logistical applications are compatible with the proposed algorithm. In addition, range-free multi-hop localization for mobile targets or mobile anchors and centralised localization in two-dimensional or three-dimensional space may be accomplished with the proposed algorithms.

Parulpreet Singh et al (2017) In their study to sensor node localization in sensor networks that operate wireless. The precise localization of nodes is exceedingly important for ensuring the overall superior performance of wireless sensor networks. A range of localization algorithms applying connectivity, range information, anchor information, computational basis, and mobility basis are examined in this piece of literature.

S. Sira Jacob, K. Muthumayil (2022),This article evaluates the MSRO-NLT, which is an altered search and rescue optimization-based node localization method for WSN. MSRO-NLT depends heavily on locating unknown nodes within the WSN in order to accomplish this objective. MSRO is an algorithm that enhances the technique's diversity through the incorporation of chaotic maps, as the conventional search and rescue optimisation (SRO) algorithm becomes susceptible to the local optima problem as the number of iterations increases.

R.Manoj Kumar, S.Sridevi (2017) Numerous algorithms pertaining to 2D and 3D localization were reflected upon, as well as localization techniques in WSN that were divided into 2D and 3D categories. An analysis of several 2D algorithms was subsequently conducted in comparison. Without significantly increasing energy consumption and computational demands, the localization algorithm must be scalable to accommodate extremely large network sizes.

Obeidat, H., Shuaieb, W., Obeidat, O. et al (2021) Various localization system technologies, such as those based on sound, optics, radio frequency (RF), inertial navigation, magnetic, satellite, and inertial navigation systems, were reviewed, along with indoor localization techniques and wireless technologies.

Netra vision and Siti Nur (2022) Their research aims to examine and debate the most well-known and influential localization algorithms that use range-based and range-free localization approaches. It has come to light through surveys that a number of algorithms, similar to parametric looping approaches, are now nearing centimetre inaccuracy.

Yassin, A., Nasser, Y., Awad, M (2017) This review focuses on interior localization techniques and ideas, however it does cover outdoor localization as well. We also cover other localization-based applications in this review, where location data is essential for estimation.

Shweta Ubnare et al (2020) a survey and taxonomy on localization for mobile wireless sensor networks. The combination of mobile platforms with wireless sensors that have limited resources introduces significant difficulties to localization in MWSNs.

Funiak et al. (2006) provided a method for localization that uses object tracking to determine the positions and orientations of ad hoc cameras within a sensor network. Everyone involved in their work operates under the assumption that a single point can adequately show any item seen through a camera lens. So, the issue of target correspondence is irrelevant to their consideration.

Aldeen, Yousra Abdul Alsahib S et al (2023) This review presents a DVHLM as a solution for WSN localization. When the node's position is dynamic and requires attention in real-time, this method is applied. Calculating coordinates, calculating distance, estimating the position of the dislocated node, and correcting the estimate are the four primary processes of the suggested method.

Zaidi et al. (2015) A proposed method for Wireless Sensor Networks (WSNs) enables localization without considering their range. This approach is designed for networks that depend on mobility, as opposed to the typically static WSN networks. By using estimation methods and locally available information, it becomes possible to determine the location of an unknown node.

Kanwar and Kumar (2021) designed a system for WSN localization that utilises the distance vector hop protocol. Displaced sensor nodes are the target of this framework's design. In order to find the nodes in the network that are actually involved in the situation, PSO techniques are also used.

Sharma and Singh (2021) The proposed method suggests using the Received Signal Strength Indication (RSSI) approach to determine the location of unknown nodes in order to estimate the locations of the sensors. Sensor networks usually depend on GPS services for localization estimates, which can result in processing complexity, energy consumption, and overhead in Wireless Sensor Networks (WSNs).

Singh and Sharma (2019) The authors proposed an effective and efficient range-free localization approach based on genetic algorithms. They were able to achieve this by adjusting the average hop size of anchor nodes and optimizing with the correlation factor and hop size using a search method.

Kaur et al. (2018) The text you provided describes two methods that were inspired by nature and implemented using enhanced variations, including two- and three-dimensional WSNs. The initial algorithms improve their estimation by utilizing the grey wolf optimization method. This technique calculates an estimate in order to find the average distance for each hop.

2.5 3D LOCALIZATION IN STATIC AND DYNAMIC SCENARIOS

Yoshida, Masaya et al (2015) To provide a novel method of three-dimensional localization using a fleet of mobile robots, one of which can clean the floor. As it cleans the floor, the mobile robot might measure RSSI instead of the anchors, reducing the load.

Ahmad, Tanveer, Xue Jun Li (2019) The purpose of this paper is to provide a 3D localization strategy that uses the famous loop invariant for division algorithm. With the help of the Parametric Loop Division (PLD) technique, which uses reference anchor points included in an outer region, parametric points are calculated.

Ahmad, Tanveer, Xue Jun Li (2020) Based on the famous Social Network Analysis technique, this study presented a new 3D localization method that doesn't need node synchronisation and instead uses trilateration clustering based on the Closeness Centrality.

Shi et al (2000)presented a way for 3D localization in WSN. Their method of localization depends on a portable beacon that sends out ultra-wideband (UWB) signals to pinpoint the precise location. Upon receiving these signals, each target node calculates the distance to the anchor node using the TOA approach.

Xu C, Yin C (2021) In this paper, A new approach to cooperative target localization measurement using several unmanned aerial vehicles is suggested as a solution to these problems. The target localization measurement phase involves a swarm of aerial vehicles (UAVs) collecting a plethora of remote sensing photos of a single ground-based target. When the objective, the image point, and the optic centre of the camera are all collinear, as is required by the principle of perspective representation, nonlinear observation equations can be constructed.

Xu Y, Zhuang Y, Gu J (2015) In their study this paper proposes an enhanced three-dimensional localization algorithm for use with existing methods. Building on the foundation of standard DV-Distance, we incorporate the concept of coplanarity and optimise the placement result using the Quasi-Newton approach.

Sesyuk, A.; Ioannou, et al (2022) explores and evaluates the present level of development in 3D indoor placement. This review covers many methodologies, strategies, and technologies that can be utilized alone or in combination to meet the cost-effective, high-resolution 3D accuracy standards of today's smart applications.

Mani, R., Rios-Navarro et al (2023) in order to reduce computational effort, memory size, and energy consumption while simultaneously increasing the number of localizable nodes and the accuracy of the data. The approach of a movable anchor node to lower hardware expenses is of interest to us. We recommend utilising the bounding box method to determine the potential area of the unknown node's location.

Ahmad T, Li XJ (2017) In their study to provide a parametric loop division (PLD) algorithm-based 3D localization approach for WSNs. The suggested method uses a network of anchor nodes to determine the exact location of a sensor node inside a certain area. The suggested method outperforms the state-of-the-art in localization accuracy by repeatedly reducing that region to its centre point.

Iram Javed, Xianlun Tang (2022) in this review proposes a more refined Savarese method to deal with the phenomenon of discontinuity in WSN node localization system. Solving a problem of singularity and improving location accuracy, the suggested approach is an enhanced version of the traditional Savarese algorithm.

Suroso, D. J.., Krisnawan (2022) This paper proposes implementing a 3D indoor localization system measurement campaign using Wireless-Fidelity (Wi-Fi) range-based and range-free methods in a real multi-story structure. Considering that Wi-Fi is present in nearly all smart devices and is placed nearly everywhere on Earth, this research is necessary.

G. Chen, X. Meng (2015) In this work, To enhance the precision and reliability of positioning, we suggested integrating Wi-Fi fingerprinting positioning with PDR, which employs a UKF algorithm. To increase the system's real-time performance and lower the resource cost of the location algorithm without reducing the positioning accuracy, the improved K-means clustering technique was presented for Wi Fi fingerprinting localization.

Ahmad, T.; Li, X.J.; Seet (2018) This paper proposed an innovative 3D localization method that borrows from a popular social network research technique; this method doesn't coordinate nodes and, instead, depends on trilateration clustering based on proximity importance.

2.6 PARTICLE SWARM OPTIMIZATION (PSO)

Kennedy (2011) developed a technique for evolutionary computation known as particle swarm optimization. The flocking behavior of birds is the basis for this technique. The PSO algorithm is easily implemented and computationally efficient. Particle solutions are employed in random locations in the search space. In order to calculate the objective function, the particle locations are randomly selected. The particles are then allowed to move randomly in the search space [Zhang et al. (2014)].

In a search space, particles are moved, and their particle best positions 'p_{best}' and 'g_{best}'are collected. An improved technique of particle swarm optimization adopted for the present extension of EL-PSO, Back Propagation for range based and DV-Hop with hybrid techniques (sequential method) optimized with improved PSO, EM-PSO.

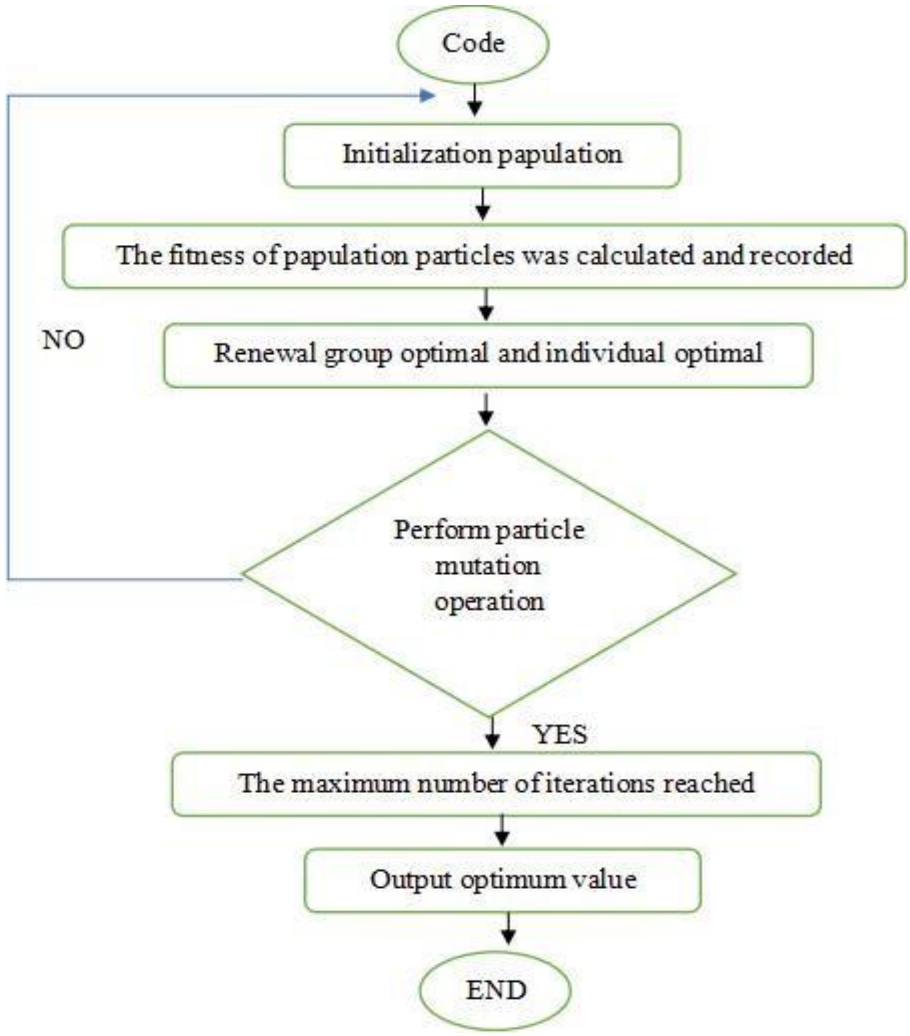


Figure:2.4 Flow chart for improved particle swarm optimization

2.6.1 Difference between PSO and Improved PSO in node localization

Due to the advantages of using a PSO algorithm in WSN location algorithms, many scholars have studied the PSO algorithm which can be applied in the localization of WSNs. In reference [2], a PSO localisation algorithm for WSNs based on adaptive inertia weight of a particle swarm is proposed. In each iteration of the PSO algorithm, the inertia weight of each particle is not the same, and is calculated according to their respective fitness values. The simulation results show that the improved method can effectively improve the positioning accuracy, and the resource requirements of WSN hardware platform are not increased. In reference [3], aiming at the problem that the error of the traditional DV-Hop algorithm is too large and the PSO algorithm is easy to fall into local optimal, a node localisation algorithm for the centroid oppositional particle swarm WSNs is proposed. The simulation results show that compared with the traditional DV-Hop algorithm, the centroid oppositional PSO algorithm has higher positioning precision and better effect, and is suitable for scenes with high positioning precision requirements.

2.6.2 Improved- PSO

A distributed two-phase PSO algorithm to solve the flip ambiguity problem, and improve the efficiency and precision. This study proposes a refinement process to fix the inaccuracy caused by flip ambiguity after the first search space is determined using the bounding box approach.Additionally, our research aims to localise unknown nodes using two or three near- collinear references.

2.6.3 State of art for experiment approach and validation

An experimental comparison between RSSI-based and multi-carrier phase difference-based localization methods have been presented in [**courtesy.S et al. 2023**]. In the experiments, random static points have been selected in a room for validation of the methods. Other hybrid localization methods based on the fusion of UWB and BLE [**Xia.J et al. 2020**], combining WiFi and UWB [**Monica.s and Borganti.F 2019**] or WiFi and BLE [**Qureshi.U et al. 2019**] have been proposed to achieve higher positioning accuracy and reduce the cost of the positioning system. Most of the proposed methods in this category have been designed for specific use cases or try to improve the accuracy under some important assumptions, which usually are not feasible in real-world applications.

Zafu Gao et al. (2023) in his research about UWB positioning in NLOS-interference circumstances, a complete method is proposed for NLOS/LOS classification, NLOS identification and mitigation, and a final accurate UWB coordinate solution through the integration of two machine learning algorithms and a hybrid localization algorithm, which is called the C-T-CNN-SVM algorithm. This algorithm consists of three basic processes: an LOS/NLOS signal classification method based on SVM, an NLOS signal recognition and error elimination method based on CNN, and an accurate coordinate solution based on the hybrid weighting of the Chan–Taylor method. Finally, the validity and accuracy of the C-T-CNN-SVM algorithm are proved through a comparison with traditional and state-of-the-art methods. (i) Focusing on four main prediction errors (range measurements, maxNoise, stdNoise and rangeError), the standard deviation decreases from 13.65 cm to 4.35 cm, while the mean error decreases from 3.65 cm to 0.27 cm, and the errors are practically distributed normally, demonstrating that after training a SVM for LOS/NLOS signal classification and a CNN for NLOS recognition and mitigation, the accuracy of UWB range measurements may be greatly increased. (ii) After target positioning, the proposed method can realize a one-dimensional *X*-axis and *Y*-axis accuracy within 175 mm, and a *Z*-axis accuracy within 200 mm; a 2D (X,Y) accuracy within 200 mm; and a 3D accuracy within 200 mm, most of which fall within (100 mm, 100 mm, 100 mm). (iii) Compared with the traditional algorithms, the proposed C-T-CNN-SVM algorithm performs better in location accuracy, cumulative error probability (CDF), and root-mean-square difference (RMSE): the 1D, 2D, and 3D accuracy of the proposed method is 2.5 times that of the traditional methods. When the location error is less than 10 cm, the CDF of the proposed algorithm only reaches a value of 0.17; when the positioning error reaches 30 cm, only the CDF of the proposed algorithm remains in an acceptable range. The RMSE of the proposed algorithm remains ideal when the distance error is greater than 30 cm. The results of this paper and the idea of a combination of machine learning methods with the classical locating algorithms for improved UWB positioning under NLOS interference could meet the growing need for wireless indoor locating and communication, which indicates the possibility for the practical deployment of such a method in the future

2.7 Conclusions and Summary

- According to the literature review, there are a few parameters that need further investigation. These are listed as following: -
- Accuracy for Localization is the most significant value. Accuracy is the maximum difference from the actual location of a sensor node during the location process. It is a challenge to achieve the maximum precision or an exact node

  position when the localization algorithms are being used. Thus, to get localizing accuracy one must use some optimization algorithms.
- UWB signals have an extremely high precise location and high time resolution. This technology has an excellent multipath effect with low

system complexity and power consumption, which can compensate for other wireless technologies' shortcomings.

- Furthermore, we offer a comparison of localization methods, highlighting their benefits, drawbacks, prices, and limitations. The localization technique, with a focus on low hardware cost and high accuracy, is Distributed RSSI based technique, it does not require any extra hardware and give much accurate results.
- The position of the mobile node in the challenging environment was also determined using this method. Future work includes the selection of Routing technique for WSN in harsh environments and constructing a test bed for localization and routing purposes to increase the life span of WSN.
- Scalability in the context of the proposed UWB localization techniques hinges on several critical factors, primarily the ability to maintain accuracy and efficiency as the network expands. Computational complexity emerges as a key concern, as the iterative refinement process and ensembled learning methods demand significant processing power, potentially becoming a bottleneck in larger networks. Efficient data aggregation and processing are also vital, requiring robust algorithms to handle the increased volume of localization data. Furthermore, communication overhead between nodes must be minimized to avoid delays in data transmission, directly impacting the accuracy of time-sensitive measurements like TDOA. Finally, the system's adaptability to dynamic scenarios, including node mobility and environmental changes, is essential for scalability, ensuring consistent performance regardless of network size or complexity.
- Ultra-Wideband (UWB) localization, while promising for its precision, faces distinct challenges that significantly impact its reliability, particularly in complex indoor environments. 1 Multipath propagation, where signals reflect off surfaces and arrive at receivers via multiple paths, introduces significant errors in time-based measurements, distorting accurate distance estimations. 2 Non-Line-of-Sight (NLOS) conditions, where obstacles obstruct the direct signal path, further exacerbate this issue, leading to signal attenuation and increased propagation delays. 3 These UWB-specific challenges, especially prevalent in dynamic and cluttered indoor settings, necessitate robust algorithms that can effectively mitigate multipath

interference and NLOS effects to achieve reliable and accurate node localization, thereby forming the core problem statement addressed in this research.

2.8 Critical analysis on approach

The analysis focuses on how these technologies enhance accuracy and efficiency in indoor positioning for wireless sensor networks (WSNs). EL-PSO and BPNN-PSO optimize positioning by leveraging advanced algorithms to process data more effectively. PSO improves parameter tuning, while ensemble learning and BPNN refine predictions, ensuring robust performance in complex environments. Optimized Ultra-Wideband Indoor Positioning Technologies for WSNs using PSO with Ensemble Learning (EL-PSO) and Back Propagation Neural Networks (BPNN-PSO) for Large Scale Methods" presents a promising approach to enhance UWB localization accuracy, particularly in expansive indoor environments, by leveraging sophisticated optimization algorithms. While these methods offer potential benefits such as improved precision, robustness against noise, and adaptability to complex settings, they also introduce challenges related to computational complexity, energy consumption, and training data requirements. Real-world implementation necessitates a careful balance between accuracy gains and the practical constraints of resource-limited sensor nodes, emphasizing the need for further research into efficient implementations and real-time performance optimization to make these technologies viable for widespread WSN deployment.

CHAPTER-III

RANGE-BASED ERROR CONTROL MODEL USING UWB FOR ESTIMATION OF OPTIMAL NODE LOCATIONIN HOMOGENEOUS DYNAMIC WSN WITH OPTIMAL POSITION

3.1 Introduction:

In this chapter, we present a range-based localization methodology for sensor node localization. We use maximum probability distribution functions to express the problem and employ an RSSI-based Time Difference of Arrival (TDOA) measurement model along with the Chan algorithm to find the coordinates of unknown nodes. Additionally, we develop a novel and precise localization algorithm for WSNs using ultra-wideband. Our study utilizes two hybrid localization algorithms, ELPSO and PSO-BPNN (Back-propagation neural networks optimized by particle swarm optimization), and compares their error optimization accuracy through simulations. Our results show a consistent improvement in localization accuracy compared to conventional algorithms available in the literature.

To construct an effective NLOS detection model, real-world data with varying degrees of multipath effects and range errors is required. This work employed the EWINE UWB LOS and NLOS datasets for LOS and NLOS data sets, respectively, to build the model. This data set was collected using ultra-wideband channels Cn number 2, which have a bandwidth of 499.2 MHz and a centre frequency of 3.9936 GHz. Results showed that preamble lengths up to 4096 enhanced the average accuracy of first-path signal recognition.

The methods used in the present research have following features with novelty

- To solve the problem of finding the source of the signal in a wireless sensor network, a new method for localising sensor nodes utilising range-based localization techniques has been proposed.
- Distance calculation using TDOA measures has been taken from the literature, and simulation has been carried out for 2D and 3D scenarios with improved Chan algorithm. The Chan algorithm could attain all TDOA by measuring and obtaining a specific analytical solution; after this, a weighted least squares algorithm was used to estimate where the nodes will be measured. By enhancing the original Chan algorithm's utility, this method discovered any mobile terminal

inside the base station signal coverage.

- The enhanced PSO technique uses a bounding box method to decrease the initial search space, however it is extremely energy intensive.
- Two methods for determining distance in two- and three-dimensional spaces are the least square (LS) and the tetrahedron (TD) algorithms.
- In addition to optimising the computed positions of the target nodes, two optimisation methods, namely ELPSO and BPNN,

3.1.1 Ensemble learning based Particle swarm Optimization

PSO theory has been divided into four main categories by recent studies: optimization problems with a single objective in continuous space, discrete space optimization problems, and discrete space optimization problems. single section optimization problem. A new algorithm called ELPSO combines GPSO, LPSO, and BBPSO to improve efficiency and effectiveness in finding the global optimum in hyperspace. The algorithm divides the population into three equal subpopulation groups. It uses guiding rules for particles to search for the global optimum. In the original PSO, particles learn from their historical best experiences and their neighborhood's best experiences. GPSO (global version) and LPSO (local version) algorithms are categorized based on how the neighborhood chooses its best experiences. GPSO takes the nearest particle's experience in global as the experience of its neighboring particle, while LPSO selects the best particle's experience from its local neighborhood based on a defined topological structure. BBPSO was proposed to improve precision and reduce parameter tuning complexity. BBPSO cancels velocity items, and uses random sampling of the Gaussian distribution to determine the particle's position. ELPSO combines these three models to avoid premature convergence and maintain population variety. The associated velocities for all PSO variants have been modified according to a new scheme.

$$V_i = w \times v_i + c_1 rand1_i \times (pbest_i - X_i) + c_2\, rand2_i \times (gbest - x_i) + c_3\, rand3_i \times (superbest_i - x_i)$$

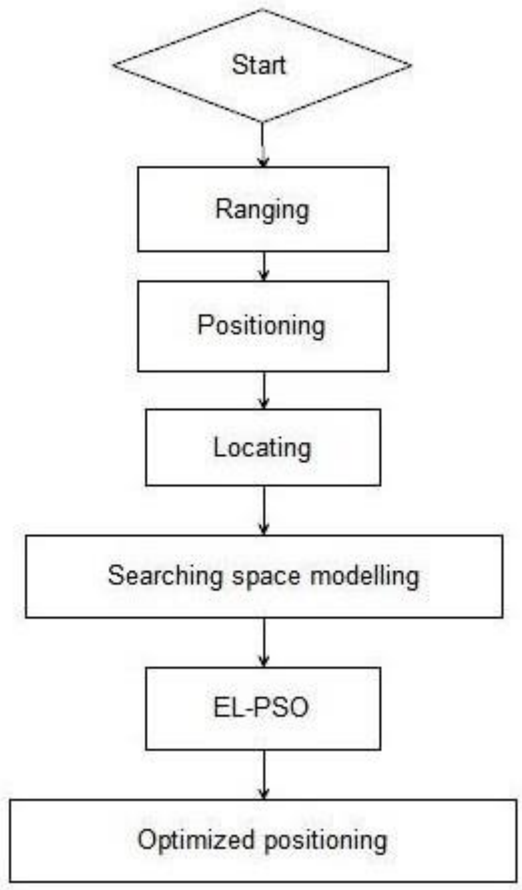


Figure:3.1 Flow chart for EL-PSO steps of Optimization

3.1.2 BPNN-PSO Optimization

The use of Neural Networks in classification is among its most important applications. Splitting neural networks into two modules allows for high accuracy. Output accuracy is generally proportional to the complexity of a neural network's architecture. By combining expected values with actual positions, the BP neural network can create a set of new positions for unknown nodes to simulate.

All reference locations are used to gather training measurements, and one model is learned for each anchor. Based on its historical data and the data now provided by sensor A2, this neural network models the data collected by a malfunctioning sensor A1 as it fails. Here, we fed the neural network a bias, along with its present and historical positions and distances. A pair of neurons in the output layer estimated the node's location. The X and Y coordinates for each interaction step were computed using the neural network. X and Y coordinates, their historical values, and the distances detected by sensor r2 were all subjected to time-series correlations in order to assess their linear temporal linkages. We observed a correlation by comparing the registered data from one sensor to the matching measured location of the second sensor.

3.2 Range based localization in selected region

An Ultra-Wideband technology-based system for wireless sensor network communication and location monitoring is the intended outcome of this research. We also evaluate tracking and range estimation techniques according to functional design, exchange of data, objective mobility, and location update latency.

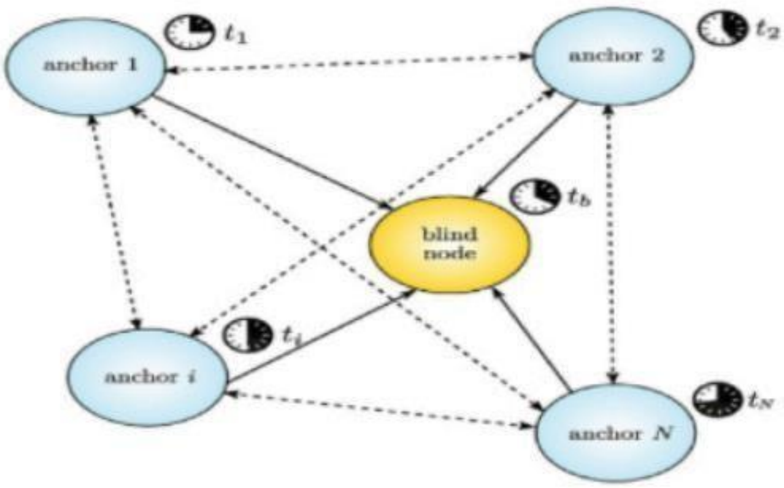


Figure :3.2 Anchor node representation

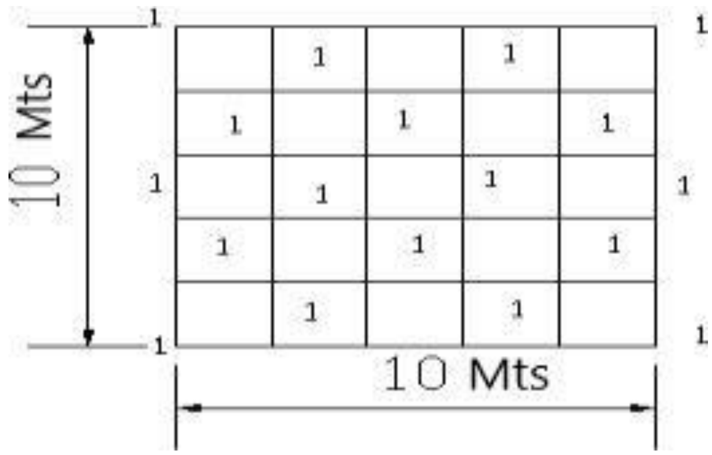


Figure:3.3 Represents the mobile nodes (target nodes) and the search space with 4 anchor nodes

During simulations and measurements, the top floors of a 10m x 10m office building were used as a reference environment. Figure 3.3 illustrates the locations of beacons in the cabins, with 1 representing a beacon.

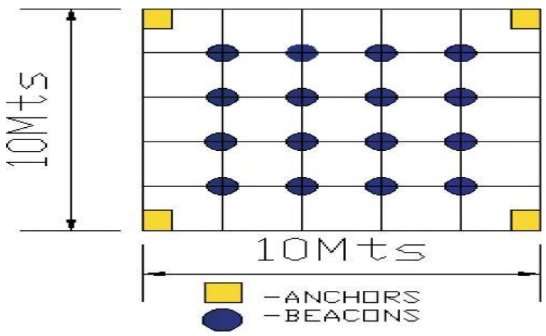


Figure:3.4 Anchor beacon placements in the selected Indoor area

3.2.1 MEASUREMENT PHASE (TDOA)

Time difference of arrival (TDOA) is a widely used range method that is second only to time of arrival (TOA) in popularity. The only two requirements for this method is time of reception and speed. There's no need to know when the communication was made to the intended recipient or when it was received. Distance between two variables and a goal can be calculated using equation 1 by comparing the times at which they arrive.

$$\Delta d = c * (\Delta t) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

In this equation, c represents the speed of light, t is the time interval between two different points of reference and Δt is the time difference of arrival.

Equation 2 can be used to get the travel distance.

$$\Delta d = \sqrt{(X_2 - X)^2 - (Y_2 - Y)^2 - (X_1 - X)^2 + (Y_1 - Y)^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Where X1 and Y1 are the known locations of the beacons, and X2 and Y2 are also known locations. By applying nonlinear regression to this equation, a hyperbolic equation can be obtained.

3.2.2. Least Square and Method of Estimation:

The TDOA-based 2D objective localization is demonstrated in a line-of-sight scenario. It was decided to use four base stations (BS1-BS4) as fixed points. The transmitter is broadcasting a signal (t) to the nearest base station, which is the antenna.

A signal is being transmitted from the transmitter (t) to the nearest base station (BS). For each iteration of i=1, 2, 3, 4, 5,... N, the signal N+1 is received by BS (i), and Yi (t) reflects the time of the positioned anchors.

The received signals are given by equation 3

$$yi(t) = ais(t - Ti) + ei(t),\ i = 1,2,3 \dots .n \dots\dots\dots\dots\dots (3)$$

an invisible sender and a mysterious recipient, located at the coordinates depicted in the diagram below. The TOA-i and (x, y) can be estimated using GPS and the n-least-squares framework. Pair wise comparison of the received signals can be used in the absence of a known reference. Pair wise estimation can be performed using a correlation function, as shown in Equation 4, where is the arrival time coordinate from the base station and i,j are the distance representatives along the x and y axes, respectively.

$$\Delta d_{(i,j)}=\nu(\tau_i- \tau_j),\ 1\le i<j \le n \dots\dots\dots\dots\dots\dots (4)$$

Where v is the final velocity, the speed of light, or the flow of a liquid. Here, N is the total number of receivers and i, j are an enumeration of all possible configurations of K pairs of receivers (where K is the total number of receivers, as given by the matrix equation) 5.

$$k= \binom{n}{2} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (5)$$

The coordinates (x, y) along the d(i,j) axis make up a waveform. Assume for the time being that the distance between the two receivers is d2, and that they are in direct line with one another. If we know the values of x and y, we can simplify d by adding the y differential to the x differential as D/2. So, we may find the hyperbolic function by solving equations 6 and 7.

$$d_2 = \sqrt{y^2 + (x + D/2)^2} \dots\dots\dots\dots\dots\dots\dots\dots (6)$$

$$d_1 = -\sqrt{y^2 + (x - D/2)^2} \dots\dots\dots\dots\dots\dots\dots\dots (7)$$

Then the Δd calculated with the equation 8 where the h differential D also includes

$$\Delta d = d_2 - d_1 = h\ (x, y, D) \dots\dots\dots\dots\dots\dots\dots\dots (8)$$

The equation 10 can be written by simplifying and rewriting equations 8 and 9.

Since h(x, y, D) is the hyperbolic function in global coordinates, we may write the differential in terms of the diagonal distance using Eq. (9).

$$D= \sqrt{(Y_i - Y_j)^2 + (X_i - X_j)^2} \quad \dots\dots\dots\dots \quad (9)$$

$$\Delta d= \sqrt{y^2 + (x + D/2)^2} - \sqrt{y^2 + (x - D/2)^2} \dots\dots\dots\dots\dots\dots\dots\dots (10)$$

The equation 11 can be written to simplify for hyperbola centroid will be

$$\frac{x^2}{a} - \frac{y^2}{b} = \frac{x^2}{\Delta d^2/4} - \frac{y^2}{\frac{D^2}{4} - \frac{\Delta d^2}{4}}=1 \dots\dots\dots\dots\dots\dots (11)$$

For a generic receiver position in the coordinate space, all that's needed is a straightforward transformation of the hyperbolic function (5) from local to global coordinates (where sin and cos represent opposite and adjacent coordinate values, and is the angle of momenta written out in equation 12).

$$\begin{pmatrix} X \\ Y \end{pmatrix} = \begin{pmatrix} X_O \\ Y_O \end{pmatrix} + \begin{pmatrix} Cos\ (\alpha) & -Sin\ (\alpha) \\ Sin\ (\alpha) & Cos\ (\alpha) \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

where $X_0 = (X_i + X_j)/2$, $Y_0 = (Y_i + Y_j)/2$ locates the center point of the receiver pair, with i, j represents center co-ordinate values.

There are N (N > 3) sensor nodes, the coordinates of the sensor nodes are known, which are $S_i = (ai,bi)^T$, $i \in \{ 1,2,...,N \}$, where $[i\ ]^t$ denotes the matrix transpose. It is $p(x,y)^T$ for the target. If the sensor can be attached to two anchors, the formula will be as follows if it doesn't fall within the above-mentioned number of instances. Considering the measuring distances as (a_i, b_i) represents to x and y coordinate with difference matrix (12), the equation can be rewritten as 13,

The coordinates of the N sensor nodes, denoted as Si= (ai,bi)T, $i \in \{ 1,2,...,N \}$, where $[i\ ]^t$ is the matrix transpose, are known. Let N > 3. The target's optimal function is p(x,y)T. If the sensor is capable of being fastened to two anchors, and the number of occurrences does not fall within the range specified above, the formula will be as follows. The equation can be simplified as 13 by considering the measurement distances as (ai, bi) represents to the x and y coordinates using the difference matrix (12).

There are N (N > 3) sensor nodes, and we have their coordinates: $S_i = (ai,bi)^T$, $i \in \{ 1,2,...,N \}$ signifies the matrix transpose. For the aim, use p(x,y)T. If the sensor has the ability to be linked to two anchors but doesn't fit into the aforementioned number of instances, the formula is as follows. The equation can be simplified as 13, where x and y are the coordinates and (ai, bi) are the distances measured.

$$ai\varphi i \approx bi \ldots\ldots\ldots\ldots\ldots\ldots\ldots (13)$$

With the error verification φi equation 14 written for the i_{th} coordinate as

$$a_i = \begin{bmatrix} x_{i1} & y_{i1} & 1 \\ x_{i2} & y_{i2} & 1 \end{bmatrix} \ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (14)$$

From the above matrix, the equation 15 written for b_i for sensor coordinate as

$$b_i = (r_{i1}^2 - x_{i1}^2)^2 - y_{i1}^2 \quad + \quad r_{i2}^2 - x_{i2}^2 - y_{i2}^2\ )^T \ldots\ldots\ldots\ldots\ldots\ldots.. (15)$$

The diagonal distance transpose matrix for sensor to node location written in the equation 16 as

$$\phi_i = [\phi_i^T \phi_i^T \phi_i]^T \text{……………………. (16).}$$

To determine the coordinates (xi, yi) at which the minimum distance to the anchor is achieved, a least-squares method was created using all of the nearby anchors. A simple formula-based geometrical method for placement can be used to create numbers. In this situation, the connecting line between the two places is the first to be discovered. The equation 17 written as is used to determine the x-coordinate.

$$x = \frac{-\gamma \pm \sqrt{\gamma^2 - 4a\eta}}{2a} \text{ …………………….. (17)}$$

The equation of the least square line, which we get after solving for a, is y = a + bx, where the values of an in equation (18) are

$\sum y = na + b\sum x$ And for b it is $\sum xy = a\sum x + b\sum x^2$ ……. (18)

The sensors first obtain location estimations, then calculate co variances by replacing these values with neighboring positions and positional distances. The sensor's location is a key factor in determining how well the various distance estimates may be combined. Take the value of the covariance, denoted by i, as an example; the estimated error can be placed at i1. The smallest error e1 is shown as the combination's final result in Figure3.5.

3.2.3. Tetrahedron 3d Method for Estimation

In order to determine the largest anchor node, the unknown node first records the RSSI value of all the anchor nodes within communication range, sorts the values from largest to smallest, and then uses the largest value.

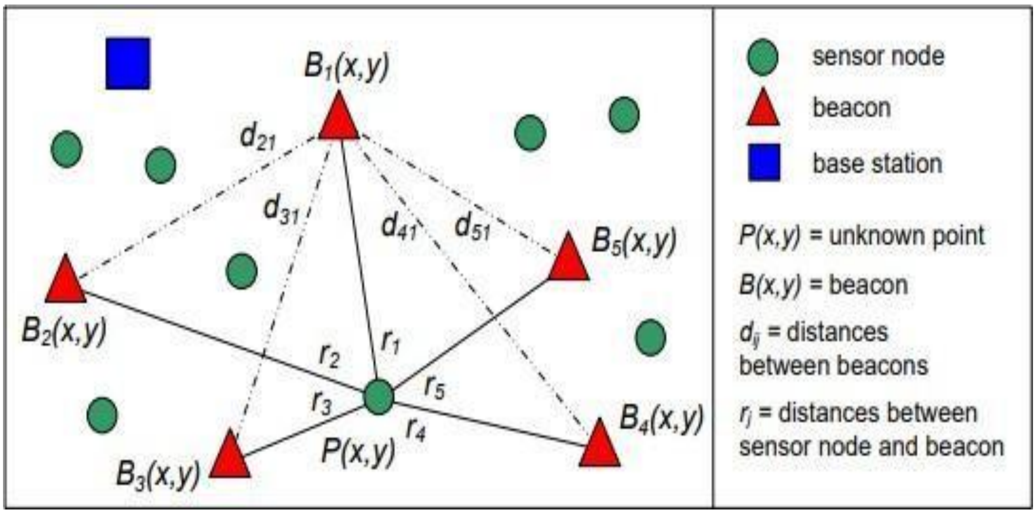


Figure :3.5 Distance Calculation between anchor and moving target nodes

The RSSI value is obtained by selecting anchor nodes from the network and communicating with them via radio and unknown nodes. In order to build a tetrahedral network, the reference nodes must be used to select a set of anchor nodes. Anchor nodes A1, A2, A3, and A4 are well-known anchors. Therefore, the distances between them are easily determined. After that, we find the radii, or distances: MA1, MA2, MA3, and MA4.

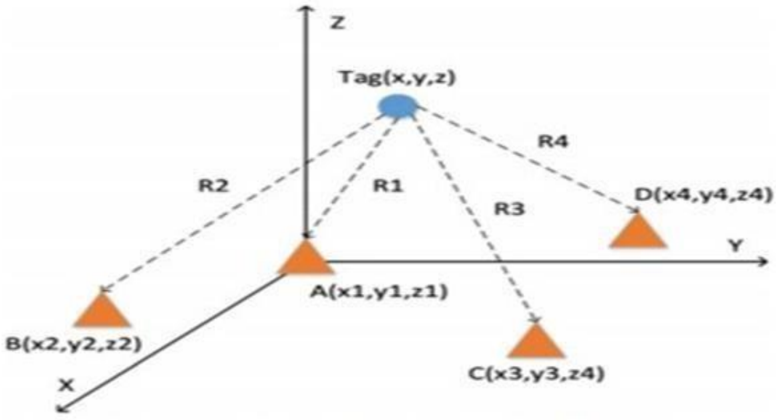


Figure: 3.6 Structure of 3D- tetrahedron with- 4 anchor nodes

Calculate the volume of A_1, A_2, A_3, A_4, $MA_1A_2A_3$, $MA_1A_2A_4$, $MA_1A_3A_4$, $MA_2A_3A_4$, the volume value V is as V_1, V_2, V_3, V4, respectively. If ($(V_1+V_2+V_3+V_4>V)$, you can determine the M in the outside of the tetrahedral $A_1A_2A_3A_4$, discard the modified tetrahedral. The formula to calculate the average distance is (1/N) ∑R(i) where N is the number of measurements and R(i) is the distance between the anchor and target nodes. When all the measurements are added up, the result is the entire distance, and the 1/N factor takes it into consideration. This formula gives a precise depiction of the distance between the two nodes by considering the average distance between the anchor and target nodes over a specified set of measurements. A more trustworthy outcome is achieved by averaging the measurements, which reduces the impact of data noise. The Cartesian coordinates of the four vertices are, (x_1, y_1, z_1), (x_2, y_2, z_2), (x_3, y_3, z_3), (y_4, x_4, z_4), rij is the distance between the vertices I and j. Then the formula for the calculation of its volume is as follows:

$$\text{RSSI} = \sum_{i=1}^{n} R(i)/N \text{ ……………… (19)}$$

Then the calculation of its volume is as derived by the matrix equation (20)

$$V= \frac{1}{6} = \begin{vmatrix} 1 & 1 & 1 & 1 \\ x_1 & x_2 & x_3 & x_4 \\ y_1 & y_2 & y_3 & y_4 \\ z_1 & z_2 & z_3 & z_4 \end{vmatrix} = \frac{1}{6} \begin{vmatrix} x_2 - x_1 & y_2 - y_1 & z_2 - z_1 \\ x_3 - x_2 & y_3 - y_2 & z_2 - z_1 \\ x_4 - X_3 & y_4 - y_3 & z_4 - z_3 \end{vmatrix} \ldots\ldots\ldots\ldots\ldots\ldots (20)$$

This process allows for calculating the centroid of each group of 4 to accurately measure the distances between the centroids and determine the size of the tetrahedron. After this calculation is complete, a new set of centroid coordinates is then used to form a new set of tetrahedral, with the remaining centroid coordinates being included in the next iteration. By accurately calculating the distances between the centroids, we can determine the size of the tetrahedron and create new sets of tetrahedra with the remaining centroid coordinates. This allows us to determine the centroid of each group of 4 efficiently and ultimately create a more precise model. Only two or three centroid coordinates remain. By determining the size of the tetrahedrons and their centroids, we can accurately calculate the distances between the centroid coordinates and divide the 3D space into smaller equal parts. This allows us to more accurately calculate the final node estimations, as we can identify the exact location of each centroid in the 3D space. In this scenario, we will take into account a communication distance of 10m, a tetrahedral shape with four anchor nodes chosen at random, and fifty unknown nodes to see if there are enough to filter out position inaccuracies. When comparing the distances between the anchor and unknown nodes, we may utilize centroid location estimates to see if any of them are within the 10m communication distance. To improve the accuracy of the final node estimates, it is possible to exclude any unknown nodes that are closer than that distance. Due to the increased likelihood of nearest neighbors for non-localized nodes, localization ratios are high.

The localization ratio (LR) is measured by equation 21, where $N_l$is the number of localized nodes andN_t is the total number of non-localized nodes.

$$LR= N_l / N_t \ldots\ldots (21)$$

In this way, the array next [0. N-1] can represent the index of a different node within the same tetrahedron (or -1 in the absence of such a node) by means of the following [p]. The information will be kept in a data structure called a mesh, and the tetrahedron will be the first node in a list of points.

The localization error per localized node is calculated by equation 22.

$$L_{error}=\sum_{i=1}^{Nl} \sqrt{(u_i - x_i)^2 + (v_i - y_i)^2 + (w_i - z_i)^2} \, /N_L \ldots\ldots\ldots\ldots\ldots (22)$$

Localized nodes in a network are the nodes whose estimated coordinates (xi,yi,zi) in virtual space are close to their actual coordinates (ui,vi,wi) in actual space, thus allowing the network to form a localized topology. The algorithm uses a heuristics-based approach which calculates the distance between the estimated coordinates and the actual coordinates. If the distance is within a certain threshold, the node is considered to be localized. The algorithm then moves on to the next node in the network and repeats the process until all the nodes have been localized.

ALGORITHM1: TARGET NODE LOCATION (2D/3D)
1. Input: define objective function (LS/ Tetrahedron) 2. Output: Localization data 3. Initialize: anchor placement-P 4. Number of targeted nodes-N 5. Define localization measured co-ordinates (x_i, y_i) (x_i,y_i,z_i) 6. Activate sensor nodes (anchors) 7. For i= least co-ordinate 8. For anchor P_i≈ check the least value of target 9. If P<Pi, then fix the value. 10. If not repeat steps 5,6,7 11. Run for the least coordinate Pi 12. End if 13. Evaluate 14. Update for measured values 15. End for **16.** End.

Least Squares is a mathematical optimization technique used to find the best-fit solution to a system of equations when there are more equations than unknowns. In localization, it minimizes the sum of the squares of the differences between the measured distances (or TDOA-derived distances) and the estimated distances based on the node's position. LS is often used to solve the set of non-linear equations that arise from range or TDOA measurements. It provides an initial estimate of the target node's position based on the measured data.

The tetrahedron method is a geometric approach used for 3D localization. It utilizes the distances between the target node and four or more anchor nodes to define a tetrahedron. The target node's position is estimated based on the intersection of the surfaces of the tetrahedron.

3.3 UWB IMPLEMENTATION

UWB prevents data loss due to multipath fading. Additionally, UWB's signal-to-noise ratio is so high that it can pinpoint the location of an object despite ambient noise. Furthermore, the signal is perfect for usage indoors due to its ability to pass through walls and other obstructions. NLOS and multi path propagation still have negative effects, although they are less severe when spread spectrum has high resolvability. This is because UWB's wide bandwidth allows for a high degree of resolution when it comes to signal propagation. TDOA readings were used to establish initial distances in this work. As its name implies, TDOA refers to the time gap between two separate arrivals. Since the speed of sound is always the same, the distance between two points can be determined by measuring how long it takes for a sound to travel from one location to the other. It is possible to properly determine the distance between two sites using this metric, which is very helpful when working with acoustic signals. Both two- and three-dimensional scenarios have been simulated using an enhanced Chan algorithm to locate target nodes. Both the speed of sound and the time it takes for sound to travel are factors in the Chan algorithm. This is carried out so that an accurate distance between two points can be determined. It can also take into account obstructions and the earth's spherical shape. Kalman filter is used to remove the energy disturbances that have been incorporated. The integration of Time Difference of Arrival (TDOA) measurements into the ELPSO (Ensemble Learning with Particle Swarm Optimization) and BPNN-PSO (Back Propagation Neural Network with Particle Swarm Optimization) algorithms is fundamental to their operation in UWB-based Wireless Sensor Networks (WSNs). Initially, accurate TDOA measurements are obtained by precisely recording the arrival times of UWB signals at multiple, synchronized anchor nodes, from which time differences are calculated. These differences define hyperbolas that constrain the potential location of the target node. Subsequently, these TDOA values serve as crucial input data for the optimization algorithms. Within the ELPSO framework, TDOA measurements are used to construct a fitness function, which guides the PSO's search for the optimal node location. The algorithm iteratively adjusts the positions of particles, each representing a potential location, to minimize the discrepancy between measured and predicted TDOA values. The ensemble learning aspect further refines these estimates by combining results from multiple PSO instances, enhancing robustness. In contrast, BPNN-PSO employs TDOA measurements as input features for a neural network, which is trained to model the complex relationship between TDOA and node location. PSO is then utilized to optimize the neural network's weights and biases, improving its accuracy. This hybrid approach leverages the neural network for initial location estimation, followed by PSO-driven refinement. To enhance the reliability of TDOA-based localization, a Kalman filter is often incorporated to mitigate noise and errors inherent in the measurements. Furthermore, both ELPSO and BPNN-PSO can be designed to address challenges like multipath propagation and Non-Line-of-Sight (NLOS) conditions by integrating models of these effects into their optimization processes. However, successful implementation hinges on accurate time synchronization between anchor nodes, optimal anchor node geometry, and careful consideration of the computational complexity, especially when deploying these algorithms on resource-constrained sensor nodes.

3.4 IMPLEMENTATION OF CHAN ALGORITHM

The TDOA data collected from the nodes is utilized by the Chan method to estimate the nodes' locations. Then, the predicted node positions are refined using a weighted least squares technique to minimize the difference between the measured and calculated TDOA values. This allows the program to accurately determine the locations of the nodes. The 2D/3D Chan algorithm calculation method is employed to improve the original Chan algorithm by enhancing one of the mathematical formulas and the two matrices. The original Chan algorithm's accuracy is limited to the area bounded by each base station. However, with the enhanced 2D/3D Chan algorithm, the coordinates of points outside the base station area can also be determined, making the algorithm more precise and efficient. Additionally, the improved algorithm can calculate the coordinates of points in higher dimensional space, expanding its applicability to various scenarios. To address this issue, we propose a least-squares method to identify measurement errors. By applying the weighted least squares method to the Chan algorithm, we derive positive and negative values for x, y, and z, based on the initial and subsequent measurements. This method provides a more accurate and reliable way of determining the location of a mobile terminal than traditional methods, as it takes into account both the first- and second-time measurements. The location precision is increased by using a weighted least-squares approach with the Chan algorithm. In addition, this technique can pinpoint any mobile terminal within the range of the base station's signal, making it ideal for a wide variety of uses. The equation (23) is an improvement on previous methods of calculating the distance between the base station and the mobile terminal

$$r_i = \sqrt{(x_i \text{â˜} x)^2 + (y_i \text{â˜} y)^2 + (z_i \text{â˜} H)^2} \qquad \ldots\ldots (23)$$

(x_i, y_i, z_i) is H is the mobile terminal's height as determined by air pressure, and the coordinate of the i^{th} base station is... Since TDOA is a three-dimensional number, it takes into account not only the time difference but also the height difference as measured by air pressure. Both the mobile terminal's height (H), determined by measuring air pressure, and the base station's three-dimensional coordinates (xi, yi, zi) are factored into the equation. Because it takes the vertical distance between the two sites into account, the distance between the observed node and the standard base station may be more accurately calculated nowadays.

$$d_i^2 = (x_i - x)^2 + (y_i - y)^2 = K_i - 2x_i x - 2y_i y + x^2 + y^2 \quad \ldots.. (24)$$

where, $K_i = x^2 + y^2$, d_{i1} is represents the difference in distance between the label and the i^{th} base station.

With i=3, it is possible to take two measurements, use equation transformation to create two equations involving two variables, and then solve for the target's required location.

When $i \geq 4$, let $R^2 = x^2 + y^2$, When the true location of Za0 is determined to be (x 0, y 0, R0), the error vector (φ) for the variables can be established. There are no known targets in the equation 25, which is written as

$$\varphi = H - G_a Z_a \ldots\ldots\ldots\ldots\ldots\ldots(25)$$

In this case, H represents the node's 3D height computation, Ga stands for the node's coordinates, and the distance matrix is expressed as follows:

$$H = \begin{pmatrix} d_i^2 - & K_1 \\ d_2^2 & K_2 \\ 3 & . \\ 1 & . \\ 2 & 2 \\ d_n^2 - & K_n \end{pmatrix}, G_a = \begin{pmatrix} -2x_1 & -2y_1 & 1 \\ -2x_2 & -2y_2 & 1 \\ . & . & . \\ . & . & . \\ . & . & . \\ -2x_n & -2y_n & 1 \end{pmatrix}, Z_a = \begin{pmatrix} x \\ y \\ R \end{pmatrix} \quad (26)$$

Let the measurement error of each reference node be Iδ , then error value of i_{th} node calculated by using the equation 27.

$$\varphi_i=d_i^2-(d_i^0)^2=(d_i^0+\delta_i)^2-(d_i^0)^2=2d_i^0\delta_i+\delta_i^2 \quad (27)$$

Referencing nodes have real values represented by di0. Weighed least squares (WLS) can be used to estimate Za in the first instance. If T is the arrival time, then equation 28 can be written as follows: for each Ga, T can be expressed as:

$$Z_a=(G_a^T ø^{-1} G_a)^{-1} G_a^T ø^{-1} H \quad ....(28)$$

Since the identity matrix is unknown, it can be used in the first estimation instead of 26. Simplifying equation 29 allows us to verify the projected value of Za as

$$Z_a= (G_a^T G_a)^{-1} G_a^T H \quad ....(29)$$

The connection between the object's estimated and real values can now be expressed using this method:

$$Z_{a1}=x_0+e_1$$

$$Z_{a2}=y_0+e_1$$

$$Z_{a3}=R_0+e_1$$

The formula is transformed into the desired error value using equation 30, where e1, e2, and e3 are estimating errors. The formula is transformed into the desired error value using equation 30, where e1, e2, and e3 are estimating errors.

$$\text{Let } \varphi_1=2xe_1+e_1^2\approx 2xe_1,\ \varphi_2=2ye_2+e_2^2\approx 2ye_2,\ \varphi_3=e_3 \quad (30)$$

then for N number of node error deviation finalized and rewritten in equation 31:

$$\varphi'^{=}H'^{-}G_a'\ Z_P \quad (31)$$

The transpose matrix with time differential error vector $Z_P$written for equation 32

$$\text{where}, H^1=\begin{pmatrix}\hat{Z}_{a1}^2\\ \hat{Z}_{a2}^2\\ \hat{Z}_{a3}^2\end{pmatrix}, G_{a^1}=\begin{pmatrix}1 & 0\\ 0 & 1\\ 1 & 1\end{pmatrix}, Z_p=\begin{pmatrix}x^2\\ y^2\end{pmatrix}.\ \varphi^1=[\varphi_1', \varphi_2', \varphi_3']^T \ ......(32)$$

T $\varphi^I=\varphi^1\varphi^2\varphi^3$ is the error vector of Z_P. The estimated value of Z_P is calculated using the equation 33 as improvement.

$$Z_P=(Ga'^T ø'^{-1} Ga')^{-1} Ga'^T ø'^{-1} H' \quad (33)$$

The location result obtained by the two WLS calculation referred to the equation 34:

$$Z=\pm\sqrt{Z_P} \quad (34)$$

There should be no difference in the sign of the selected (x, y, z) in Zp and in the Zp selected inside the placement region as a solution to a problem.

3.4.1 Filtration: Kalman filtering is an iterative procedure that begins with forecasting and concludes with improvement. As part of the forecasting procedure, estimates of several factors will be made. The update process, on the other hand, entails bringing data up to date in light of new developments. What happens in a Kalman filter is described below.

An N beacon node is placed at various times in the field in order to determine the mobile node's range signal. You must know (Xn,Yn), where n = 1,..., N, to determine the location of the nth beacon node. Mobile nodes move randomly in a 2D plane, with state vectors x(k) = [x(k) y(k)]. Applying this formula to a mobile node allows us to characterize its location and speed at each time step. At the time step denoted by k, the values 1, 2, 3, 4, etc., are equivalent. The value of x(k) changes at each iteration interval. The (xm, ym) coordinates of a beacon are from (m = 1) to (m = M) because there are M beacon nodes in the network. With the state vector x(k), a mobile node randomly moves this two-dimensional plane. The locations and velocities of the mobile nodes are represented by X(k) and Y(k), respectively, at every time step k = 1,..., K. Equation 35 describes the change in position X(k) of a mobile node at time step k.

$$k, \hat{x}_k = F_k x_{k\text{â˜}1} + B_k u_k (35)$$

In which circumstances as an example, consider the relationship between the ith hour's temperature (ti) and humidity (hi): the correlation coefficient l (T, H) is the value of this relationship. The average humidity levels are denoted by T and H, respectively. You may express the filtration in terms of equation 37 and the node's position in terms of equation 36, where Pk is the post estimate error covariance. Humidity and temperature are filtered along the x-vector in the following way: 38, where H is the relationship between the state Xk and the measurement Zk.

$$P_k = F_k P_{k\text{â˜}1} F_k^T + Q_k (36)$$

$$K' = \frac{P_k H_k^T}{H_k P_k H_k^T + R_k} (37)$$

$$x_k = \hat{x}_k + K' (z_k \text{â˜} H_k \hat{x}_k) (38)$$

The position node can calculate after filtration by using the simplified equation 39

$$P_k = P_k (1\text{â˜} K' H_k) (39)$$

To determine the accuracy, use the formulas 40 and 41 for the temperature at the node, TN for the number of nodes, and the filtered value; to get the precision, use the formulas 42 and 43 for the redundant verification. Algorithm 3 offers the algorithmic flow for localization with filtration.

$$\text{Accuracy:} \frac{TP + TN}{TP + TN + FP + FN} (40)$$

$$\text{Precision:}\frac{TP}{TP+TN} \quad (41)$$

$$\text{Recall:}\frac{TP}{TP+FN} \quad (42)$$

$$IoU = \frac{X\text{âˆ©}Y}{X\text{âˆª}Y} \quad (43)$$

3.4.2 Difference between Chan and improved Chan algorithm

After obtaining the first patch of (x,y) they can reiterate in the calculations again for more improvement. This can take from 1 to 4 cycles in many of the cases.

we can observe that the resulting values of (x) and (y), are dependent on the value of (R1) which is the distance between the home base transceiver station and the mobile station. We propose a non- iterative Chan-Ho that adopts a different term that improves the accuracy. We constructed a new value, which utilizes the different values resolved from two base stations transceivers, to estimate the right distance and therefore obtain the most accurate position. This value is derived from an expression that relates the error on each direction (vertical and horizontal) to the distance obtained, using the following expressions:

$$\frac{(x_i - xo_i)}{R_i}: \text{ for the x-axis ratio, and} \quad \text{……(44)}$$

$$\frac{(y_i - yo_i)}{R_i}: \text{ for the y-axis ratio.}$$

To generate a symmetrical matrix, we will multiply the matrix by its transpose. Then to understand the characteristics of this matrix we will obtain the eigenvalues, by calculating the trace; which will lead to the nearest accurate solution.

The final value obtained will be corrected by taking the square root of the arithmetic mean of the trace, as following:

$$\omega = \sqrt{\frac{tr(Q'Q)}{2}}$$

Therefore the new calculation system will be:

$$\begin{bmatrix} x \\ y \end{bmatrix} = -\begin{bmatrix} X_{2,1} & Y_{2,1} \\ X_{3,1} & Y_{3,1} \end{bmatrix}^{-1} \times \left\{ \begin{bmatrix} R_{2,1} \\ R_{3,1} \end{bmatrix} \omega + \frac{1}{2} \begin{bmatrix} R_{2,1}^2 - K_2^2 + K_1^2 \\ R_{3,1}^2 - K_3^2 + K_1^2 \end{bmatrix} \right\} \quad \text{…….(45)}$$

Therefore the new calculation system will be:

$$\begin{bmatrix} x \\ y \end{bmatrix} = -\begin{bmatrix} X_{2,1} & Y_{2,1} \\ X_{3,1} & Y_{3,1} \end{bmatrix}^{-1} \times \left\{ \begin{bmatrix} R_{2,1} \\ R_{3,1} \end{bmatrix} \omega + \frac{1}{2} \begin{bmatrix} R_{2,1}^2 - K_2^2 + K_1^2 \\ R_{3,1}^2 - K_3^2 + K_1^2 \end{bmatrix} \right\} \quad \text{....(46)}$$

Algorithm -2 Position optimization with improved Chan algorithm

1. Input: Measured target co-ordinate
2. Output: Measured data deviation
3. Initialize: Update anchor node list, Checking Pi, transmission

    1(a). Checking the node ID

4. Sending feedback signals 3. Establishing relevant matrices

    3(a). Establishing the estimation matrix

    3(b). Establishing the distance matrix

5. Constructing the approximation matrix
6. Repeating the preceding steps until all matrices are formed

Output Position of the non-anchor node

(1. Picking up the distance range from the anchor node list

2. Calculating the final distance matrix via Ls = Tsp.

3. Positioning the transmission node.

4. Filtration)

7. Return the position information of the target sensor node as the outcome
8. End if
9. Evaluate the position
10. Update best position Pi
11. End for.
12. End.

3.5 FLOW CHART FOR PROPOSED METHODS

Nodes in the network that are localized to NL have actual coordinates of (ui, vi, wi) and estimated coordinates of (xi, yi, zi) in virtual space. Here is the computational flow for localizing target flow nodes:

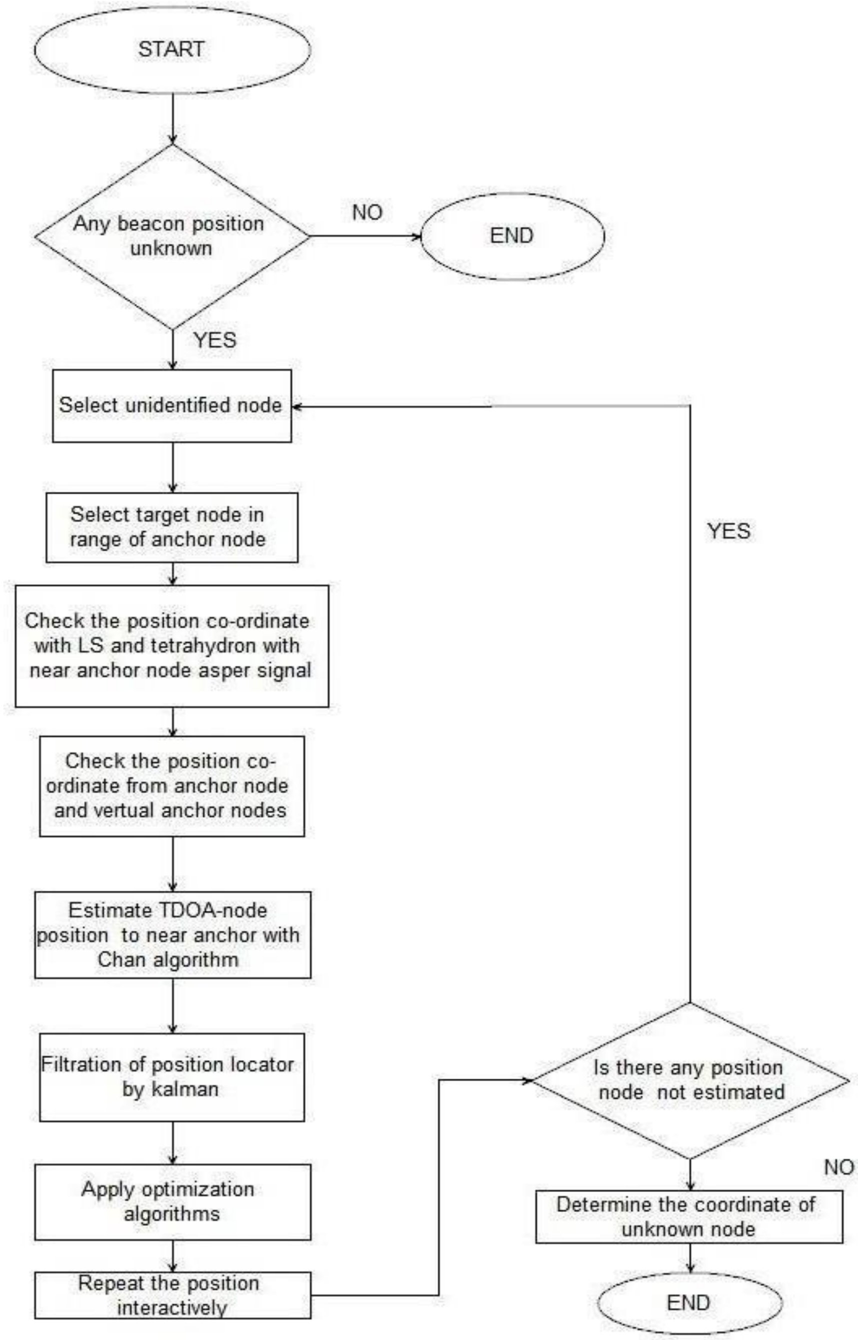


Figure: 3.7 flow chart for proposed system of optimization

This enables for more precise estimations of node coordinates and less inaccuracy due to interference. An "improved" Chan algorithm, when integrated with ELPSO and BPNN-PSO, significantly enhances the localization accuracy and robustness of UWB-based WSNs by providing more reliable initial TDOA-based position estimates. This improvement, likely achieved through noise mitigation and NLOS error correction, translates to a better starting point for the computationally intensive ELPSO and BPNN-PSO algorithms, allowing them to focus on refining the location with greater precision. By reducing computational complexity and enhancing the quality of initial estimates, the improved Chan algorithm facilitates faster convergence and improved overall localization performance, particularly in challenging indoor environments.

3.6 OPTIMIZATION WITH IMPROVED PSO:

A recalculation of measurement for node localization using improved PSO compared to traditional PSO with Ensemble learning. This approach is beneficial because it can effectively explore the parameter space by using multiple particles to explore different parts of the space. In addition, the system is able to make more informed decisions using the data acquired by the particles thanks to the Ensemble learning method. Because of this, the algorithm is now more trustworthy and precise. The placement of particles in the parameter space indicates potential solutions to the design optimization challenge. Finding local optima would have been impossible without the algorithm's exploration of the parameter space. Ensemble learning also allows the algorithm to weigh the different particles according to their performance and make better decisions. This helps the algorithm to come up with more accurate and reliable solutions than it would if it was only using a single particle. A particle's velocity is determined by its movement across the parameter space. In addition to requiring fewer parameters and faster convergence, the PSO approach is relatively straightforward. As part of algorithm 3, the mass-less particle swarm is used to find the optimal location.

Assuming m particles are searching for the best solution in D-dimensional space using PSO, the location of the i^{th} particle in the swarm is determined as Xi = (Xi1, Zi2, · ··············· XiD). Each particle searches for the global optimal solution within the search space independently. The location of the i^{th} particle is determined according to the position of its neighbors, as well as its own velocity, which is updated at each iteration. Every possible location is evaluated using the objective function to determine whether the particle's position is correct.

The optimal location of the particle is: Pbest(i) = (Pi1, Pi2, ············ PiD), record the optimal coordinate currently searched in the entire particle swarm as: Gbest = (Pg1, Pg2, ·········· PgD). In dynamic mode of node localization,the velocity of the particle defined as

$$V_{id}=w*V_{id}(t)+c_1r_1(Pbest_{id}(t)-x_{id}(t)+c2r2(gbest_{id}(t)- x_{id}(t) \quad (47)$$

Algorithm-3 Pseudo code for optimization improved PSO- 3D

%% Output: the initial calculated value of the target position (x,y,z)

1. For $1 \le i \le N$ Do %% i is each particle
2. Initialization of particles
3. End
4. Do
5. For $1 \le i \le N$ Do
6. If fitness (X_i) > p-best i Then p-best-i = X_i;
7. End
8. If %%p-best-i is the best position of $^{i\text{-}th}$ particle
9. End
10. For g-besti=opti$\{p\ best_i i_1 \le i \le N\}$%% optimum value
11. For $1 \le i \le N$ Do
12. If fitness (X_i) > p-best i Then p-best-i = X_i;
13. Update particle velocity and position according to the equation-9
14. If pbesti>gbesti
15. Then g best i = p best i;
16. End if
17. End for
18. End

Algorithm -4 Optimization of nodes using improved Particle swarm optimization

1.Initialization of swarm size i.eno.of particles inside the selected area. Selected anchor nodes measuring target node for localization.

2 Evaluate the fitness function of each particle If fitness (X_i) > p-best i

3. Select the g- best among all the p-best

4. Update g- best If pbesti>gbesti

5. Then g best i = p best i;

6. Update particle velocity and position according to the equation-1

7. Repeat the steps 3-6 until objective function defined

PSO implementation for localization

```
While (not timeout)

{

Listen for and collect anchor nodes' information
if (discover 3 or more anchor nodes in its neighborhood)
{//MODE 1

CALL procedure LOCALIZATION
}
}

//MODE 2

Get original anchor nodes' information from the packet broadcast by the closest neighbor anchors

if (discover 3 or more anchor nodes)

{

CALL procedure LOCALIZATION
}

else

{

Set as an orphan node

}


Procedure LOCALIZATION

{
Use PSO to estimate the location and become an updated anchor node

Broadcast the estimated location and the location data of original anchor nodes
Localization complete and exit
}
```

The technique is a fast method of finding coordinates since it minimizes the time spent calculating the distances between locations. In addition, two optimization methods, namely ELPSO and BPNN, have been developed to optimize the calculated target node positions: least square (LS) and TD (tetrahedron).

The choice of ELPSO (Ensemble Learning with Particle Swarm Optimization) and BPNN-PSO (Back Propagation Neural Network with Particle Swarm Optimization) for optimized UWB indoor positioning in WSNs is justified by their potential to address the inherent challenges of accurate localization in complex environments. ELPSO is selected for its ability to enhance robustness and accuracy by leveraging the strengths of multiple PSO variations, effectively mitigating errors caused by noise and multipath effects, which are prevalent in UWB systems. BPNN-PSO, on the other hand, combines the adaptive learning capabilities of neural networks with the global search efficiency of PSO. This hybrid approach allows the system to learn complex signal propagation patterns and non-linear relationships, crucial for handling NLOS conditions and dynamic changes in indoor environments, while PSO ensures efficient exploration of the solution space. Both algorithms are chosen to improve the accuracy and reliability of UWB localization, especially in large-scale deployments, where traditional methods often fall short, by providing a robust and adaptable solution to the specific challenges of indoor positioning.

3.7 OPTIMIZATION USING ELPSO

By combining the efforts of many individual learners, ensemble approaches enhance the generalizability of a single learner's progress. A random sampling process is used to construct subsets of the original dataset. Subsets are then used for training purposes. Finally, a vote mechanism is used to integrate the subsets. The figure displays the 2D and 3D TDOA node localization optimization based on ELPSO.

There are two ways in which you can represent particle i's position in N-dimensional space: by using the vectors [X_{i1}] and [X_{i2}] and by using vectors Vi = [V_{i1}, V_{i2}, V_{i3}, V_{i4}]. The evaluation function and the particle's personal best position (p_{best}) and current location (Xi) provide each particle a fitness value based on its experience. Additionally, we recorded the optimal location (gbest) for every particle, which is determined by the experiences of our peers. The particle revises its location and velocity accordingly based on its best guess at its future movement, which it gets from its own or other particles' best guesses. Pbest represents the data classification closest to the optimal approach's Pbest value. One common approach to classifier combining in algorithms is the relative majority voting method. Here is how to get the H1(x) prediction output using ensemble learning: the coordinates of the optimal X are denoted by i and j.

$$H_1(x) = C_{\underset{l}{argmax} \Sigma_i^L = 1\, h_i^j(x)} \quad .. (48)$$

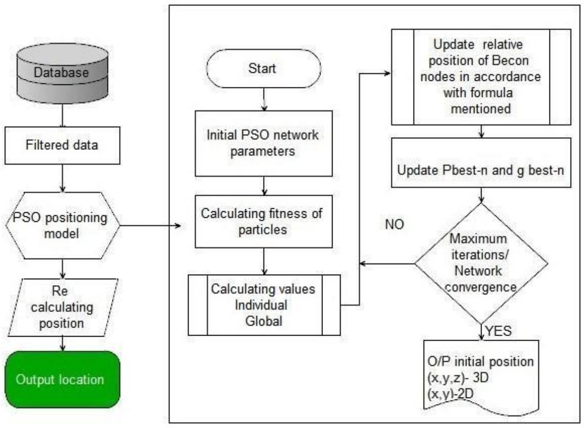


Figure 3.8: ELPSO based optimization with TDOA node localization 2D & 3D

Following the categorization of N data points in particle swam, the estimated location of P was double-checked for the nearest neighbouring value of P (Xi, Yi). With N particles distributed across this area with a distance L between each particle and each base station, and with each ith particle and jth target having an observed distance R between them, we may derive the following fitness function:

$$f(p_i) = (L_A^i - R_A^i)^2 + (L_B^i - R_B^i)^2 + (L_C^i - R_C^i)^2 + (L_D^i - R_D^i)^2 \quad (49)$$

When f = 0, Pi achieved the optimal solution, i.e., Pi exactly located in the position of target.

To find the mean and standard deviation of the solutions in the appendices. When f3, f5, f6, f7, f8 and f13 are considered, the ELPSO achieves the best possible solution in these functions.

Algorithm 5- Psuedo code for migration/ mutation

1. for solution for each particle **do**
2. for each particle initiate $v_{i,}$ x_i
3. Calculate P_i for each particle **do**
4. **Set** gen=0 and ω=0.9
5. If ω=0.9-0.5 the gen/generate d=1
6. For each dimension d update S_{best}
7. end if
8. end if
9. end for
10. end for

11. for solution for each particle **do**
12. for each dimension d [$v_{id=}$ min(v_{max}), max v_{max}] ; x_{id}=x_{id}+v_{id}
13. Update X_{id}=N (P_{best}+ S_{best})/2
14. If d≤size **do**
15. then d=d+1 repeat steps 12-14
16. Else update $S_{best(}$ min) and $P_{best(}$ min)
17. Update X_{id} (min)

18. Update d (min)
19. end if
20. End for

Algorithm 6- Optimization of node localization using improved Ensemble learning Particle swarm optimization
1. Initialize swarm size, number of particles in indoor 2. Evaluate the objective function; target node distance from near four anchor nodes 3. Check the position of P was verified for the lowest near by value of P (X_i, Y_i) from N number of nodes. 4. Calculate space following a distance L from nearest anchor 5. Update nearest particle position i^{th}andj^{th} from anchor 6. P_{best} from nearest 3 anchor nodes. 7. Apply fitness function using equation 45 8. When f = 0, Pi achieved the optimal solution, i.e., Pi exactly located in the position of target. 9. Consider f1,f2, f3.............. fn for node localization 10. Update g_{best} from N number of $P_{best;}$ until P_{best}> g_{best} 11. Repeat 3 to 8 until desired value of localization distance achieved 12. Update and fix distance.

3.8 BPNN-PSO OPTIMIZATION

In addition to devoting a great deal of time to researching all the possible static patterns for classes, solving classification challenges also demands a considerable level of research. As shown in Figure 3.9, the swarm (neuron) is initialized by assigning it to a random place and velocity, and it is also given a set of potential solutions as it travels through hyperspace. The two-module design of neural networks allows for very accurate TDOA estimate propagation. The PSO preliminarily optimizes the parameters of BPNN to avoid the BPNN falling into the local optimal solution. In the PSO algorithm, the potential solution of each optimization problem is imagined as a point in a x-dimensional space which is called a particle. The particle moves around in the search space according to simple mathematical formulae regarding the particle's position and velocity. Each particle's movement is also influenced by its local best-known position and the global best known position, which are found by the fitness function.

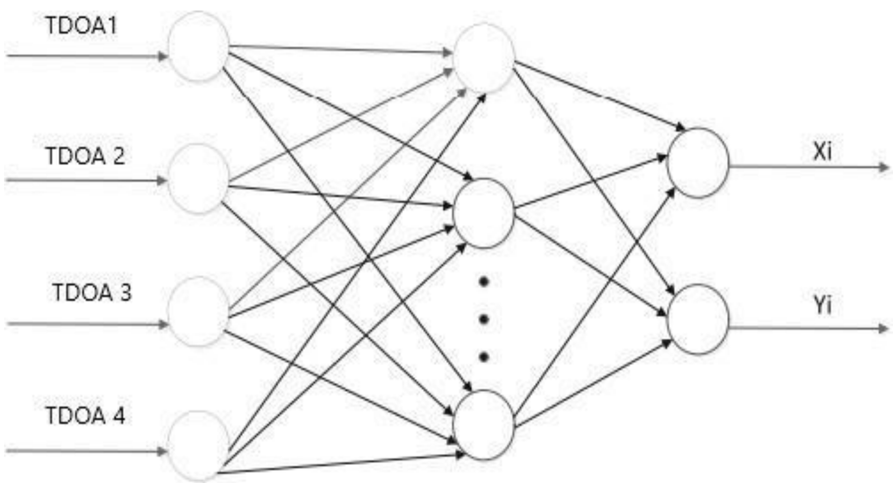


Figure 3.9: Network process of TDOA in BPNN for real optimal values

Input layer: The majority of the input values for each model are utilized in the training set, while the test set accounts for the remaining 20%.

Hidden layer: A neural network's hidden-layer performance is impacted by the network's node count. In general, the accuracy of a network's output is directly proportional to its architectural complexity. This study uses 8 neurons due to the compromise approach's fast training time and high accuracy. To get close to any non-linear precision function, the Tan(h)-Sigmoid activation function is applied.

Figures 8 and 9 show the output layer, which is made up of two 2D places estimated minimum and four 3D positions estimated minimum, respectively. First, train the BP neural network using the expected values and its current location; second, construct a group of the unknown node's new positions to simulate.

For instance, CM2 represents places without line-of-sight access and CM1 represents residential areas with line-of-sight. By utilising all of the SNR values, the BP neural network may achieve optimal RMSE performance in the CM1 and CM2 channels through hybridization with PSO.

The optimization of measuring values evaluated by neurons in error prediction was carried out on 17% of the samples under consideration from a total of 300 sample datasets. Ten from each set will be used for training and validation purposes. Three different training scenarios are considered in the study:

Step-1: Using previous data and real-time data from sensor A2, this neural network imitates the data collected by a failing sensor A1 in the event of its failure. In order to train the neural network, we feed it the exact same data that we intend to use. A neural network is made up of an input layer, an inner layer (often called a hidden layer), and an output layer. The data is received by the input layer, which then shows them to the other neurons. With four inputs (including the bias, which was assumed to be a value of 1), the input layer in this investigation required four neurons to function properly. Thus, this neural network received past positions $(x(t-1), y(t-1))$, $(x(t-2), y(t-2))$, current and past distances calculated from sensor A2$(r(t), r(t-1), r(t-2))$.

Step-2: The location of the node was estimated in the output layer using two neurons. The inertial tendency and movement speed are determined by comparing the last two positions using the machine-learning algorithm. The results of the algorithm are the X and Y coordinates of each interaction step. This neural network is depicted in the photograph.

Step-3: The purpose of conducting time-series connections was to evaluate the linear temporal linkages between the X and Y coordinates, their historical time values, and the distances measured by sensor r2. At each stage, we saw one of the most current discrete values for that variable. The exact speed of the target determined how long it took to progress through each level.

Step-4: Searching at the mean error compared to the median reveals that the statistical distribution of mistakes is symmetrical, possibly with a very short left tail, similar to the behaviour of the X-axis.

Step-5: Since the estimated position falls within the active sensor radius and the prior position/trajectory is known, the virtual sensor could temporarily operate as the actual sensor. In the event that one of the sensors used in the trials stopped functioning, this replacement would continue to function properly regardless of how far away the original sensor was from the nodes that were considered. Using the MATLAB function corr(), we can find the relative positions of the sensors by comparing their time series position vectors, which comprise the positions detected by the sensors. This correlation was discovered by comparing the recorded data for all of the measured locations.

A model of a backpropagation neural network with 20 hidden layer neurons was developed using a dataset consisting of 100 data points. The test data set was used to test this network, and the calculated root mean square error was 0.1040 m. Additionally, the network was trained using a dataset consisting of 300 data points. Using the same dataset once more, this time produced a root-mean-square error of 0.0350 m. The simulated positions of each node and their actual positions in the two scenarios (100 data points training and 300 data points training). It was then tested with the test dataset after training a radial basis function network model with 100 neurons in the hidden layer using the same dataset with 100 data points.

They used the BPNN method to build a framework for UWB sensor network object detection. In Figure3.6, How well the localization method worked in comparison to the least-squares estimator. Backward error propagation and weight correction. There is a computation of neuron error gradients in the output layer:

Network model	Number of training data points	RMSE
BPNN	100	0.1040m
	256	0.0978m
	361	0.0350m
PSO- BPNN	100	0.1820m
	256	0.0732m
	361	0.0137m

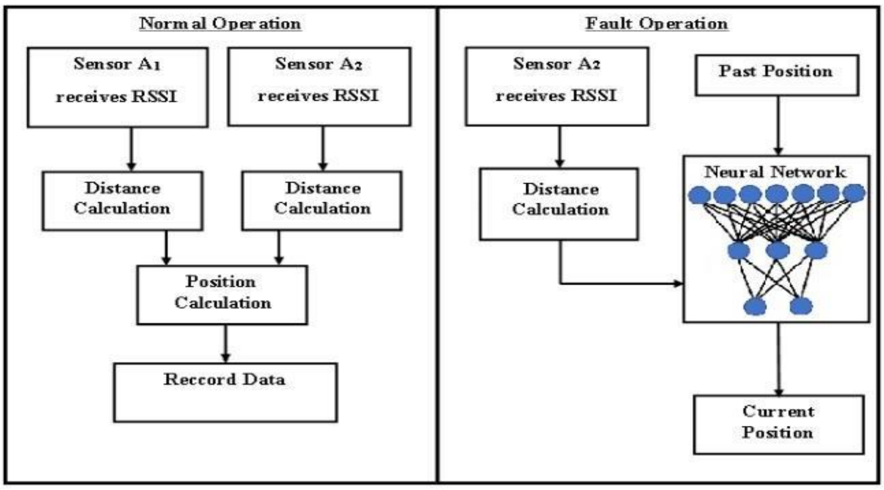


Figure 3.10: Optimal path flow chart by using BPNN

Training and validation sets consist of 10 each. Three training scenarios are examined in the study:

- Every anchor is trained with measurements at every location, and there is only one model learned for each anchor (A=0).
- All anchors are measured for training (M=0), and a single model derived from the training measurements is applied for all anchors (A=1).
- Every second reference location is measured during training to build separate models for each anchor (A=0).

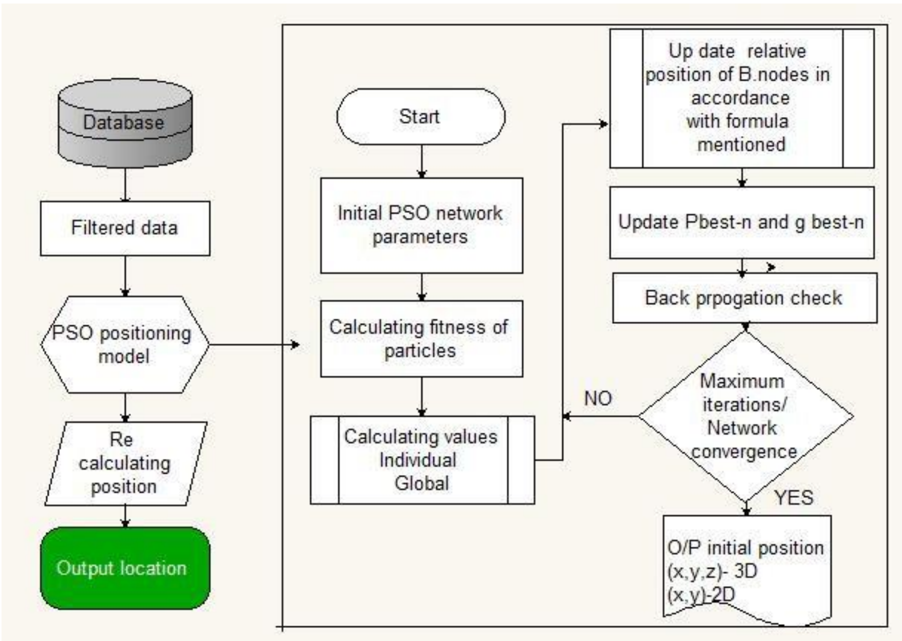


Figure 3.11: Flow Chart For BPNN- PSO Implementation for Optimal Error Variance

UWB sensor networks can detect objects using the BPNN approach. Using the localization strategy vs, the least-squares estimator and how well it performs. Backward error propagation and weight correction. During the output layer, neuronal errors gradients are determined:

A steady result has been the goal of earlier neural networks (such as the Multilayer Perception) P(d|x), which is an extension from the conventional neural network method and is a probability density function (pdf) of the inter-node distance depending on the pre-processed feature vector. $\vec{x}= (x_1, \ldots, x_n)^T$ [1,..., x˜M] ^{T} to get better output data.

$$x_m = -1 + \frac{2(x_m - x_{m,min})}{x_{m,max} - x_{m,min}} \quad m= 1\ldots\ldots M \qquad (50)$$

When estimating absolute localization coordinates using fitness functions, the final m values are stored in the anchor environment.

	Algorithm -7 for Training
Input	Target data, distance between each of the sensor node with anchor nodes (3 anchor nodes are used here)
Output	Input to Hidden layer and Hidden to Output layer weight matrices
Initialization	Initialize all the weights with the random values
1	while the stopping condition not satisfies do
2	Calculate the net input using $I_M - \sum w_{km} * O_k + \theta_m$
3	Apply the activation function 0_m = f (I_k) Propagate the error in backward direction
4	Calculate the error for output layer using Err_m = $O_m(1 - O_m)(T_m - O_m)$
5	Calculate the error for hidden layer using Err_m = $o_m(1 - O_m) \sum Err_t * W_{mt}$
6	Update the weights and θ(bias) values using $\Delta W_{km} = l * Err_m * \theta_m$ $W_{km} = W_{km} + \Delta W_{km}$ $\Delta\theta_{km} = l * Err_m$

	$\theta_{km} = \theta_{km} + \Delta\theta_{km}$ Check for the Stopping conditions
7	if (ΔW_{km} < threshold) OR (total number of iterations exceeds a certain predefined value) then
8	Stop
9	end if
10	end while

Algorithm 8 for Testing	
Input	Weights and bias produced during training phase, location of sensor nodes placed at random locations
Output	Target locations with minimum localization error Initialization: Initialize the required variables
	Calculate the distance between each of the sensor node with the anchor nodes
	for each hidden and output layer unit do
	Calculate the net input $I_m = \Delta W_{km} * O_k + \theta_m$
	Apply the activation function 0_m = f (I_k)
	end for
	Calculate the Testing Error

ELPSO (Ensemble Learning with Particle Swarm Optimization) exhibits a computational complexity driven primarily by the iterative nature of PSO and the added overhead of ensemble learning. The PSO component involves a population of particles navigating the solution space, with each particle's fitness evaluated through a function that typically incorporates TDOA measurements. This evaluation becomes increasingly complex in environments with multipath and NLOS effects, requiring intricate calculations. Moreover, the ensemble approach, which combines results from multiple PSO runs or variations, significantly amplifies the computational load, as each PSO instance must be executed and their outputs aggregated. The overall complexity of ELPSO, therefore, scales with the number of particles, iterations, and the size of the ensemble, making it more computationally demanding than standard PSO.

BPNN-PSO (Back Propagation Neural Network with Particle Swarm Optimization), on the other hand, presents an even higher computational burden, particularly during the neural network training phase. The backpropagation algorithm, integral to neural network learning, necessitates numerous forward and backward passes through the network, updating weights and biases based on the training data. This process is inherently complex and scales with the network's architecture and the size of the training dataset. Furthermore, the integration of PSO to optimize the neural network's parameters adds another layer of computational overhead, as the neural network calculations are repeatedly executed within the PSO's iterative framework. The combined effect makes BPNN-PSO exceptionally computationally intensive, especially when dealing with large networks or complex environmental conditions, surpassing the complexity of ELPSO. Number of particles taken as 50 with 4 anchor nodes with a range of 100 sqmts.

3.9 RESULTS AND DISCUSSION:

The search location is defined on all measured targets in the conventional UWB localization technique from the previous section. Very little modification is required to incorporate the suggested approach into the Fusion Center's current hardware architecture. Use of ultra-wideband (UWB) indoor localization and the suggested algorithms ELPSO and BPNN were evaluated in a 10 m x 10 m squared model. Two estimators were employed to handle the produced nonlinear equations.

Due to its low energy consumption and great accuracy, this algorithm was found to be better than other popular algorithms. The study doesn't prove the algorithm's efficacy, but it shows how it could be a good starting point for finding WSNs; furthermore, 3D UWB indoor localization is an improved version of 2D. Similarly, in a 10 m × 10 m × 10 m cube region, there are four base positions at the same coordinates: A (Xa, Ya, Za)

= (0, 0, 10), B (Xb, Yb, Zb) = (0, 10, 10), C (Xc, Yc, Zc) = (10, 10, 10), and D (Xd, Yd, Zd) = (10, 0, 10) within the same vicinity. See Figure 10 for the 3D indoor localization setup. In the course of the exam, the 50 target locations (x, y, z) are distributed evenly. Similarly with the two-dimensional example, the optimization step is applied to all objectives.

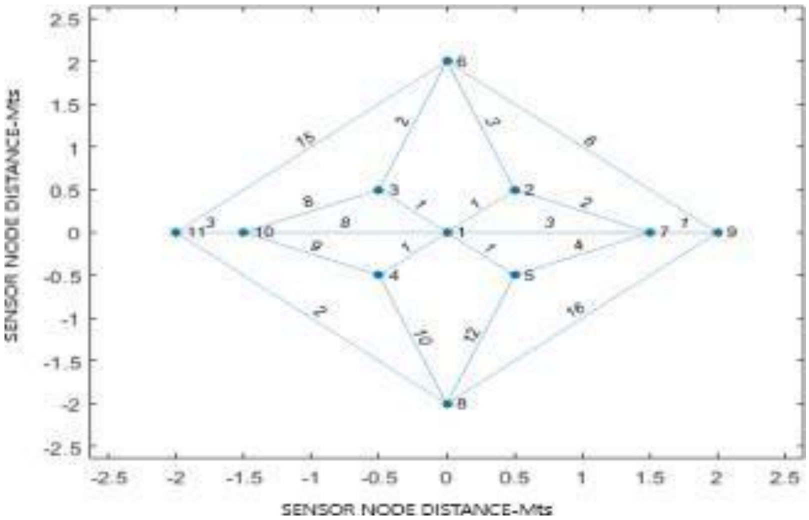


Figure 3.12: Localization Pattern from Anchor to Dynamic Nodes In Indoor Network In 3D Environment.

TABLE 3.1: CO-ORDINATE VALUES OF LOCALIZATION OF 2D POSITIONING

Target	Target position(m)	Measured position(m)	Measured error(cm)	Optimized position(m)	Error after Optimization(cm)
1	(-4.50, -4.50)	(-4.86, 4.58)	3.664	(-4.470, -4.462)	3.964
2	(-4.50, -3.50)	(-4.96, -3.24)	5.28	(-4.462, -3.471)	3.762
3	(-4.50, -2.50)	(-4.62, -2.84)	2.36	(-4.472, -2.481)	2.864
4	(-4.50, -1.50)	(-4.31, -1.62)	2.04	(-4.662, -1.534)	3.212
5	(-4.50, -0.50)	(-4.16, -0.82)	4.62	(-4.528, -0.504)	0.3164
6	(4.50,4.50)	(4.96,4.38)	4.744	(4.474,4.530)	2.862
7	(4.50,3.50)	(4.82, 3.64)	3.396	(4.51,3.489)	0.3244
8	(4.50,2.50)	(4.32, 3.10)	4.324	(4.62,2.536)	3.784
9	(4.50,1.50)	(4.51,1.72)	0.584	(4.46,1.471)	0.3564
10	(4.50,0.50)	(4.16, 0.82)	4.424	(4.462,0.535)	0.3458
11	(-3.50, -4.50)	(-3.70, -4.58)	2.064	(-3.533, -4.468)	3.246
12	(-3.50, -3.50)	(-3.92, -3.24)	4.876	(-3.465, -3.535)	3.524
13	(-3.50, -2.50)	(-4.12, -2.84)	7.356	(-3.462, -2.54)	3.824
14	(-3.50, -1.50)	(-3.10, -1.62)	2.8	(-3.529, -1.536)	3.2462

15	(-3.50, -0.50)	(-3.20, -0.82)	4.1	(-3.539, -0.571)	3.662
16	(3.50,4.50)	(4.16, 4.82)	4.356	(3.458,4.536)	3.9432
17	(3.50,3.50)	(3.80, -4.18)	5.4	(3.536,3.474)	3.2412
18	(3.50,2.50)	(3.92, -2.64)	4.32	(3.534,2.478)	2.8214
19	(3.50,1.50)	(4.12, -1.24)	4.86	(3.471,1.536)	3.1242
20	(3.50,0.50)	(3.10, -0.42)	4.32	(3.466,0.537)	3.4246
21	(-2.50, -4.50)	(-2.60, -4.58)	4.18	(-2.541, -4.529)	3.0816
22	(-2.50, -3.50)	(-1.92, -3.24)	5.46	(-2.465, -3.533)	3.5642
23	(-2.50, -2.50)	(-2.12, -2.84)	7.25	(-2.540, -2.531)	3.8946
24	(-2.50, -1.50)	(-2.90, -1.62)	6.87	(-2.456, -1.537)	3.6343
25	(-2.50, -0.50)	(-3.20, -0.82)	5.64	(-2.54, -0.471)	3.5421
26	(2.50,4.50)	(2.16, 4.82)	6.28	(2.532,4.539)	3.7825
27	(2.50,3.50)	(1.80, 4.18)	6.41	(2.539,3.458)	3.6462
28	(2.50,2.50)	(2.92, 2.64)	6.639	(2.460,2.532)	3.8716
29	(2.50,1.50)	(2.12, 1.24)	4.620	(2.53,1.466)	2.9645
30	(2.50,0.50)	(3.10, 0.42)	4.822	(2.522,0.474)	2.8654
31	(-1.50, -4.50)	(-1.70, -4.58)	5.367	(-1.541, -4.682)	3.2416
32	(-1.50, -3.50)	(-0.92, -3.24)	3.125	(-1.465, -3.537)	0.3564
33	(-1.50, -2.50)	(-1.12, -2.84)	4.623	(-1.472, -2.534)	3.3230
34	(-1.50, -1.50)	(-2.10, -1.62)	4.821	(-1.529, -1.536)	3.2464
35	(-1.50, -0.50)	(-1.20, -0.82)	4.129	(-1.472, -0.531)	2.9815
36	(1.50,4.50)	(1.16, 4.82)	3.424	(1.534,4.699)	2.8242
37	(1.50,3.50)	(1.80, -4.18)	37.624	(1.465,3.538)	3.6587
38	(1.50,2.50)	(1.92, -2.64)	34.396	(1.54,2.458)	3.9874
39	(1.50,1.50)	(1.12, -1.24)	4.044	(1.535,1.532)	3.4824
40	(1.50,0.50)	(1.10, -0.42)	4.064	(1.47,0.531)	2.9108
41	(-0.50, -4.50)	(-0.70, -4.58)	2.064	(-1.532, -4.463)	3.1253
42	(-0.50, -3.50)	(-0.92, -3.24)	4.364	(-1.459, -3.538)	3.7846
43	(-0.50, -2.50)	(-0.52, -2.84)	3.404	(-1.54, -2.462)	3.6422
44	(-0.50, -1.50)	(-1.10, -1.62)	6.144	(-1.47, -1.473)	3.2654
45	(-0.50, -0.50)	(-0.70, -0.82)	3.024	(-1.532, -0.469)	2.9321
46	(0.50,4.50)	(1.16, 4.82)	7.624	(1.469,4.532)	3.1258
47	(0.50,3.50)	(1.40, 4.18)	13.624	(1.537,3.529)	3.6547
48	(0.50,2.50)	(0.92, -2.64)	4.396	(1.46,2.54)	3.7624
49	(0.50,1.50)	(0.62, -1.24)	1.876	(1.541,1.536)	3.5212
50	(0.50,0.50)	(1.20, -0.42)	12.9	(1.466,0.532)	3.4632

Note: m -meters cm- centimeters

An indoor object's initial measurement triggers the creation of a search space, analogous to a 2D setup, around that target. Illustrations 3.9 and 3.10 We can now see the search space in three dimensions due to the object. At its activation, the swarm distributes at random within this sphere.

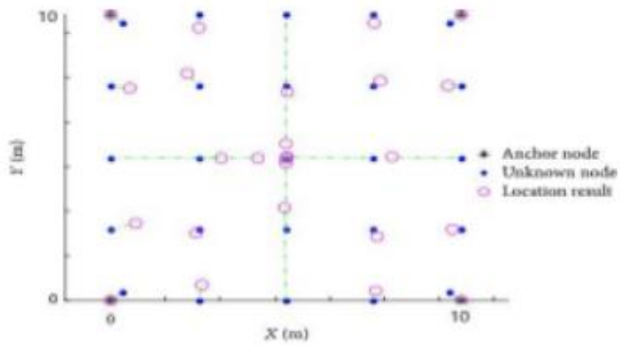


Figure 3.13: Regular deployment of nodes localization

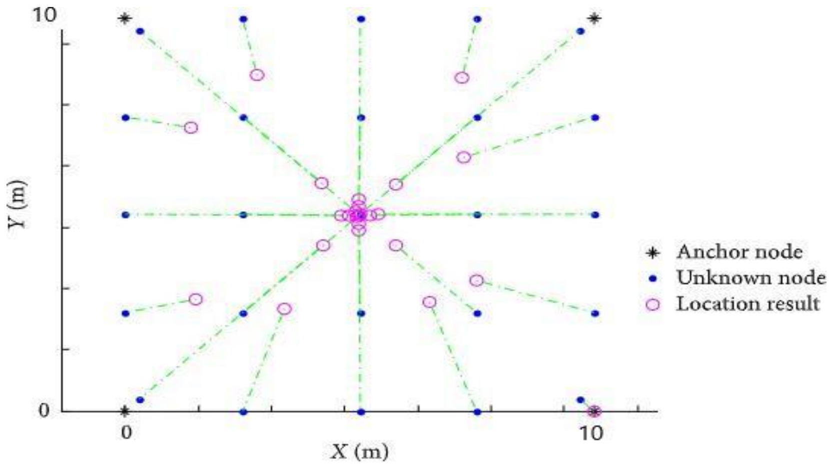


Figure 3.14: Least square deployment of nodes localization

Compared to other target nodes, the velocity and mobilization of particles at the anchors and neighbouring sensors exhibit extremely little error in both the 2D and 3D measurement instances.

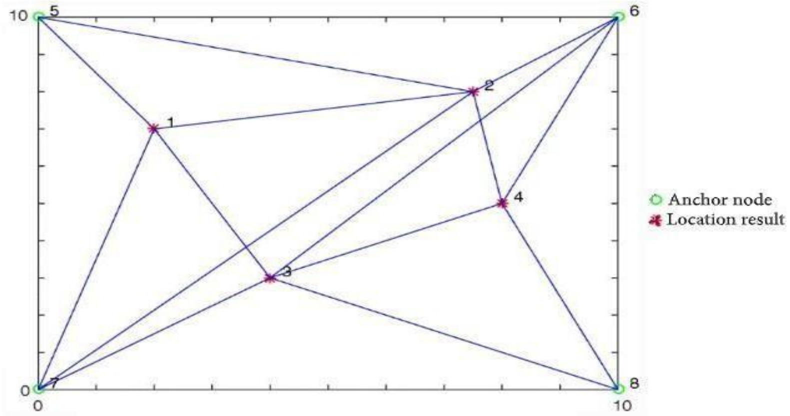


Figure 3.15: Least square deployment of nodes localization

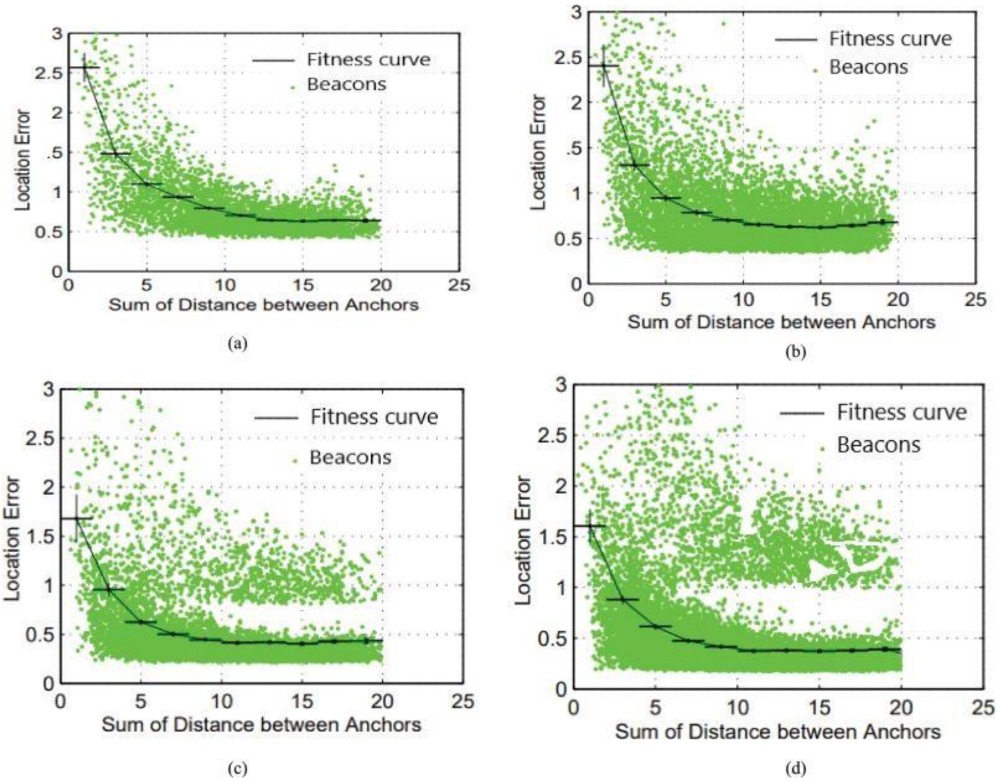


Figure 3.16: Comparison of various algorithms at various positions. (a) A fitness graph of beacon measurements at position 1. (b) A fitness graph of beacon measurements at position 2. (c) Measurement of beacon at position 3. (d) Fit graph of beacon measurement at position 4.

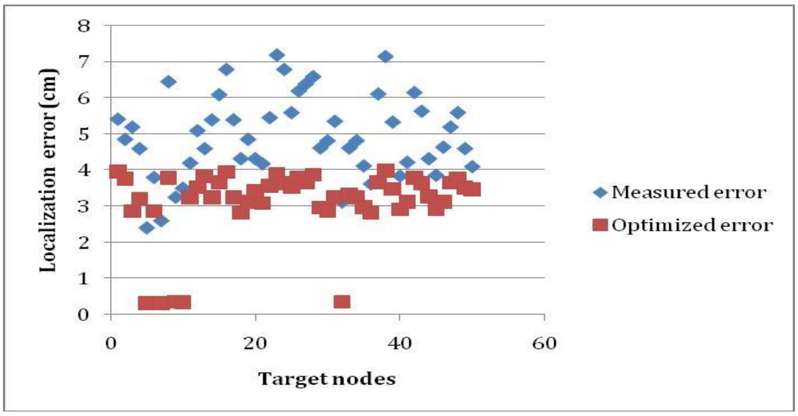


Figure 3.17: Comparison of measured localization error with optimized error in 2D scenario

An indoor object's initial measurement triggers the creation of a search space, analogous to a 2D setup, around that target. We can now see the search space in three dimensions thanks to the item. At random intervals, this sphere releases the swarm. Optimal error values for certain nodes are found in figures 3.16 and 3.17, and the beacon's mobilisation time with respect to the anchor node is close to where the two anchor nodes are located. At the present, close to the wall, RMSE does not show much variation.

Table 3.2: Co-ordinate values of Localization of 3D positioning

Target	Target position (m)	Measured position(m)	Measured error(cm)	Optimized position(m)	Error after Optimization (cm)
1	(-4.50, -4.50,4.8)	(-4.86, -4.58,4.2)	7.264	(-4.832, 4.541,4.762)	3.351
2	(-4.50, -3.50,4.6)	(-4.96, -3.24,4.6)	4.716	(-4.924, 3.468,4.631)	3.252
3	(-4.50, -2.50,4.4)	(-4.62, -2.84,3.9)	4.856	(-4.581, 2.486,4.343)	2.264
4	(-4.50, -1.50,4.2)	(-4.31, -1.62,4.4)	1.961	(-4.532, 1.472,4.241)	3.112
5	(-4.50, -0.50,4.0)	(-4.16, -0.82,3.6)	6.024	(-4.522, -0.552,3.94)	0.2964
6	(4.50,4.50,3.8)	(4.96,4.38,3.5)	5.64	(4.978,4.42,3.714)	2.462
7	(4.50,3.50, 3.6)	(4.82, 3.64,3.8)	3.8	(4.534,3.582, 3.628)	0.2844
8	(4.50,2.50,3.4)	(4.32, 2.10,3.2)	3.8	(4.451,2.403,3.434)	3.324
9	(4.50,1.50,3.2)	(4.51,1.72,3.1)	1.485	(4.515,1.478,3.204)	0.3164
10	(4.50,0.50,3.0)	(4.16, 0.82,2.9)	4.524	(4.298,0.503,2.994)	0.3058
11	(-3.50, -4.50,2.8)	(-3.70, 4.58,2.6)	3.906	(-3.544, -4.538,2.76)	2.946
12	(-3.50, -3.50,2.6)	(-3.92, -3.24,2.5)	4.32	(-3.534, 3.443,2.562)	2.824
13	(-3.50, -2.50,2.4)	(-3.32, -2.84,2.3)	4.112	(-3.458, 2.572,2.364)	3.314

14	(-3.50, -1.50,2.2)	(-3.20, -1.62,2.1)	4.936	(-3.417, 1.546,2.231)	3.0162
15	(-3.50, -0.50,2.0)	(-3.28, -0.82,1.95)	5.341	(-3.419, 0.614,2.033)	3.222
16	(3.50,4.50,1.8)	(3.36, 4.82,1.87)	5.468	(3.444,4.592,1.832)	3.3132
17	(3.50,3.50,1.6)	(3.80, 3.18,1.52)	4.781	(3.572,3.454,1.634)	3.0112
18	(3.50,2.50,1.4)	(3.72, 2.64,1.3)	4.13	(3.565,2.545,1.36)	2.014
19	(3.50,1.50,1.2)	(3.12, 1.24,1.15)	4.22	(3.434,1.457,1.171)	2.9242
20	(3.50,0.50,1.0)	(3.10, 0.42,1.08)	3.61	(3.419,0.436,1.044)	3.1246
21	(-2.50, -4.50,0.8)	(-2.60, -4.58,0.9)	3.828	(-2.541, -4.53,0.825)	2.816
22	(-2.50, -3.50,0.6)	(-1.92, -3.24,0.75)	4.824	(-2.389, -3.44,0.643)	3.2442
23	(-2.50, -2.50,0.4)	(-2.12, -2.84,0.58)	5.61	(-2.38, -2.564,0.483)	3.3946
24	(-2.50, -1.50,0.2)	(-2.90, -1.62,0.3)	5.388	(-2.594, 1.541,0.232)	3.2343
25	(-2.50, -0.50,0.0)	(-2.20, -0.82,0.15)	5.12	(-2.442, -0.571,0.04)	3.1421
26	(2.50,4.50,4.8)	(2.16, 4.82,4.2)	5.44	(2.398, 4.545,4.832)	3.2825
27	(2.50,3.50,4.6)	(2.80, 3.18,4.6)	5.860	(2.584, 3.434,4.633)	3.1462
28	(2.50,2.50,4.4)	(2.92, 2.64,3.9)	5.726	(2.592, 2.567,4.366)	3.3716
29	(2.50,1.50,4.2)	(2.12, 1.24,4.4)	4.027	(2.396, 1.412,4.228)	2.6645
30	(2.50,0.50,4.0)	(2.10, 0.42,3.6)	4.323	(2.422, 0.477,3.981)	2.2154
31	(-1.50, -4.50,3.8)	(-1.70, -4.58,3.5)	4.969	(-1.582, 4.534,3.764)	3.0216
32	(-1.50, -3.50,3.6)	(-0.92, -3.24,3.8)	2.624	(-1.299, 3.464,3.638)	0.3164
33	(-1.50, -2.50,3.4)	(-1.12, -2.84,3.2)	4.121	(-1.413, 2.548,3.364)	3.0230
34	(-1.50, -1.50,3.2)	(-1.10, -1.62,3.1)	4.320	(-1.426, 1.545,3.162)	3.1464
35	(-1.50, -0.50,3.0)	(-1.20, -0.82,2.9)	3.824	(-1.399, 0.564,2.962)	2.6815
36	(1.50,4.50,2.8)	(1.16, 4.82,2.6)	3.027	(1.434,4.452,2.763)	2.3242
37	(1.50,3.50,2.6)	(1.80, 3.18,2.5)	2.122	(1.566,3.432,2.568)	3.1587
38	(1.50,2.50,2.4)	(1.72, 2.64,2.3)	5.969	(1.581,2.554,2.359)	3.3874
39	(1.50,1.50,2.2)	(1.12, 1.24,2.1)	4.241	(1.421,1.461,2.168)	3.2824
40	(1.50,0.50,2.0)	(1.10, 0.42,1.95)	4.089	(1.399,0.459,1.972)	2.5108
41	(-0.50, -4.50,1.8)	(-0.70, -4.58,1.87)	2.113	(-0.545, 4.534,1.845)	2.9625
42	(-0.50, -3.50,1.6)	(-0.62, -3.24,1.52)	1.94	(-0.541, -3.459,1.56)	3.1846
43	(-0.50, -2.50,1.4)	(-0.52, -2.84,1.3)	3.504	(-0.538, 2.563,1.366)	3.2422
44	(-0.50, -1.50,1.2)	(-1.10, -1.62,1.15)	6.169	(-0.942, 1.553,1.162)	3.0654
45	(-0.50,-0.50, 1.0)	(-0.70, -0.82,1.08)	3.088	(-0.544,-0.538,1.032)	2.7321
46	(0.50,4.50, 0.8)	(1.06, 4.82,0.9)	6.724	(0.884, 4.542, 0.832)	2.8254
47	(0.50,3.50,0.6)	(0.40, 4.180,0.75)	6.224	(0.462, 3.988,0.633)	3.1324
48	(0.50,2.50,0.4)	(0.72, 2.64,0.58)	2.72	(0.682, 2.541,0.431)	3.0622
49	(0.50,1.50, 0.2)	(0.62, 1.24,0.3)	2.844	(0.539, 1.465, 0.239)	3.5212
50	(0.50,0.50,0.0)	(1.20, 0.42,0.15)	5.925	(1.094, 0.468,0.094)	3.2132

Note: m -meters cm- centimeters

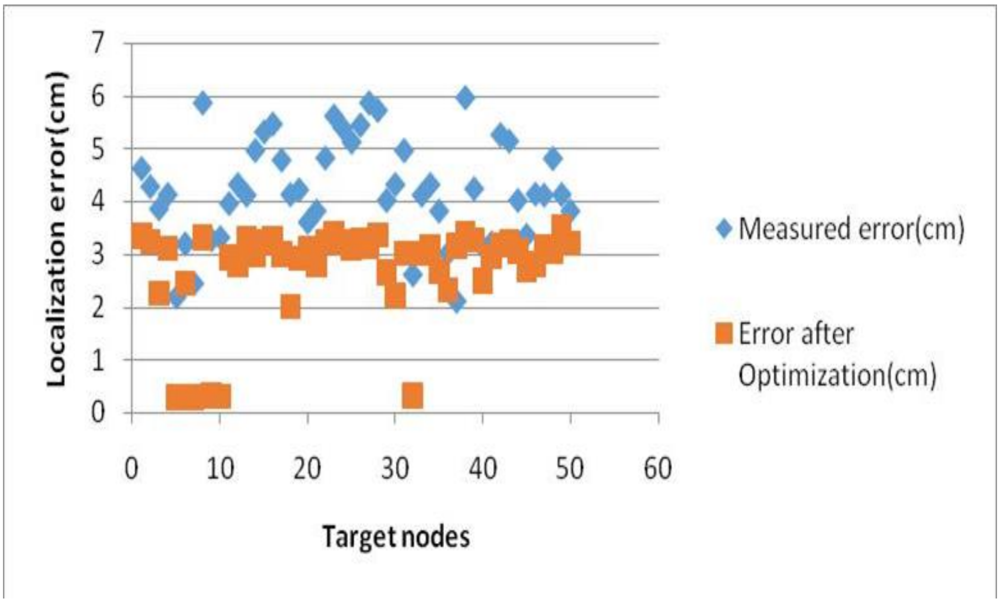


Figure 3.18: Error fitness deviation after repeatable test with dynamic nodes

The position has been optimized to minimize localization error, as shown in Figure 3.15. The figure indicates a large location error in relation to the conditions for anchor placement. By incorporating additional swarm optimization approaches, the Chan algorithm measures and filters out nodes whose dynamic momentum changes randomly. To determine the precise measured value with anchors, all location errors are found in centimeters under dynamic conditions. To determine their precise location, a group of unknown nodes estimates their distance from three distinct anchors. The Receive Strength Signal Indicator (RSSI) can be used to determine the distance between the anchor and an unknown node. In most cases, PSO has already converged on the best solution, causing it to become stuck in the local optimal problem.

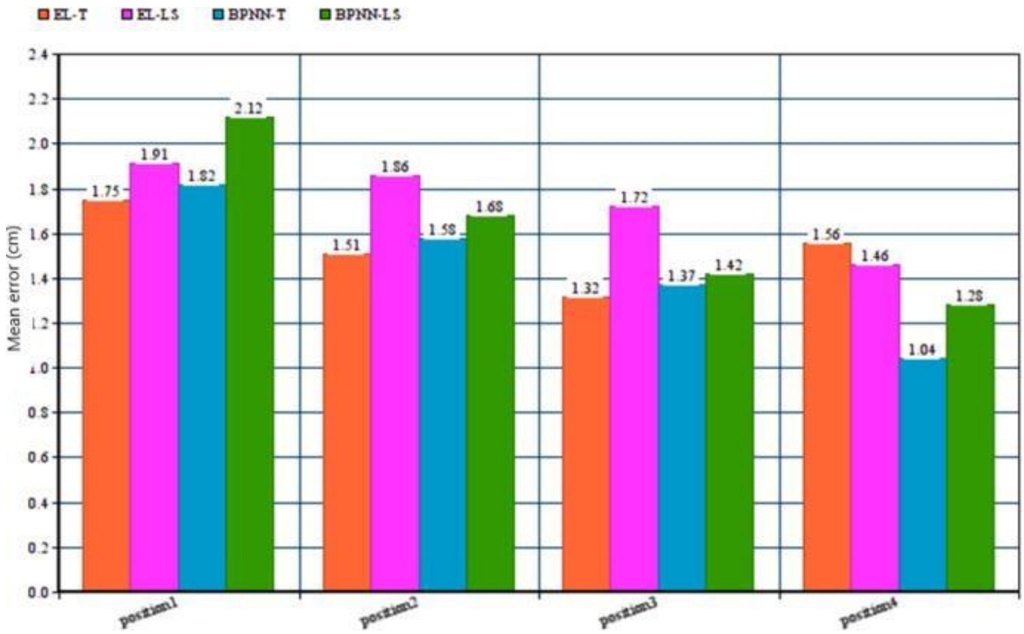


Figure 3.19: Comparative analysis of various algorithms at various positions

To minimize localization error, we optimized this location using data that showed significant errors in anchor placement conditions. By adding swarm optimization methods, the Chan algorithm filters out nodes with random changes in dynamic momentum. Location errors are measured in centimeters under dynamic conditions to determine the exact value with anchors. Unidentified nodes use distance estimates from three anchors to figure out their location.

TABLE 3.3: CO-ORDINATE VALUES OF LOCALIZATION OF 3D POSITIONING

Optimal technique – method	Movement position	Transmission Range	Max localization Error-cm	Min localization Error-cm	Average LE cm	Total number of located nodes
ELPSO-(T)	1	100M	3.964	0.4320	1.75	50
	2	100M	3.2462	0.3214	1.51	50
	3	100M	2.8654	0.2862	1.32	50
	4	100M	3.4632	0.4938	1.56	50
ELPSO-(LS)	1	100M	4.2365	0.3164	1.91	50
	2	100M	4.6432	0.3458	1.86	50
	3	100M	3.7564	0.3244	1.72	50
	4	100M	3.2146	0.3564	1.46	50
PSO-BPNN-(T)	1	100M	3.8492	0.2654	1.82	50
	2	100M	3.3291	0.3216	1.58	50
	3	100M	2.9654	0.2196	1.37	50
	4	100M	2.2132	0.2456	1.04	50
PSO-BPNN-(LS)	1	100M	4.4263	0.3165	2.12	50
	2	100M	3.6419	0.3427	1.68	50
	3	100M	2.9465	0.2696	1.42	50
	4	100M	2.7222	0.2421	1.28	50

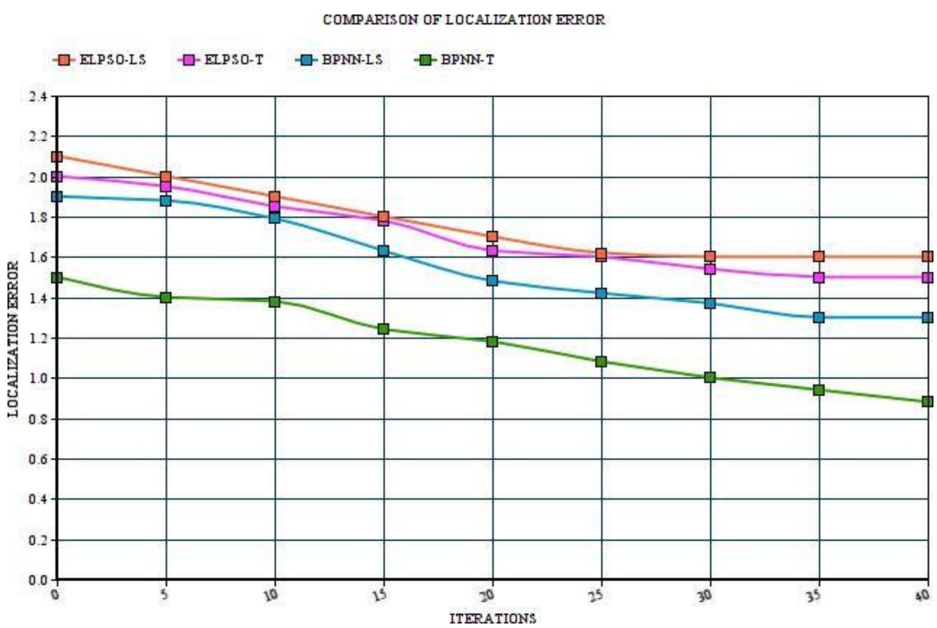


Figure 3.20: Comparison of localization error for all optimal techniques

In Figure 15, the comparison results of different 3D error localization methods with those incorporating back propagation neural networks are displayed. The results indicate a minimum change of 1.02 cm, which is relatively low when following the suggested procedure. The use of hybrid 2D/3D algorithms, along with UWB networks for indoor localization placement and dynamic interpretation of measured values, has proven to be quite effective. Simulations were conducted to determine the density of anchor nodes. A new approach is being employed to minimize localization error in a UWB setting within an indoor network, utilizing several optimal strategies.

The results of comparing 3D with back propagation neural networks to others reveal the lowest values of error localization, as illustrated in figure 3.20 and indicated in table 3.3. With just a 1.02 cm variation, the results were relatively low following the suggested procedure. Hybrid algorithms combining UWB, indoor localization, and positioning, as well as the dynamic interpretation of measured values, have shown promising results. The density of anchor nodes was determined in the scenarios that were performed. A new approach is used to reduce the localization error in a UWB indoor network using several optimal methods. The results demonstrated in this research demonstrate that the RMSE for node localization is significantly enhanced when the TDOA method is applied in conjunction with neural networks. When the region involved is small and the node density is large, this strategy works well. A basic 3D ranging-error model that depends on the orientation of neural networks is presented in this paper. The distance, together with the computed direction, elevation, and azimuth, were inputs needed by the chosen BPNN model. We show and explain the experimental data and outcomes of configuring the BPNN model. An increase in the hidden layer neuron count results in a drop in BPNN model error when tested on training data. In this 3D situation, BPNN achieves a 97.5% success rate with a 95.29 percent validation rate and a 93.73 percent accuracy rate.

3.10 CONCLUSION

An entirely new approach to optimization is presented in this study based on the use of ultra-wideband signals (UWB) for real-time indoor localization. Solution of the interior location problem can be achieved by using an optimization problem. Ensemble learning involves learning from the experiences of their own particles, their neighbors' experiences, and the experiences of other swarms. Using this new learning technique, particles can develop their own search areas that are more promising and improve indoor location accuracy. The existing technology can be used to MATLAB to execute both 2D and 3D UWB indoor locating procedures. One computational engine that may be implemented in MATLAB can control the transmitters and receivers at the same time. Continuous optimization of sound waveforms and related reception filters allows for adaptation to the ever-changing monitoring environment. Since wireless sensor networks with several anchor nodes aren't uniformly distributed, a Chan algorithm is more suited for fast-moving targets since it requires less processing power. Algorithms based on PSO Optimization combine a combination of ensemble learning and back-propagation neural networks with a Kalman filter for Chan localization. Using a back propagation neural network for localization with PSO yielded the best results across all hybrid combinations examined. The results demonstrated a smallest change of 1.02 cm and were relatively low using the suggested procedure. In hybrid 2D/3D algorithms, UWB networks with indoor localization placement and dynamic interpretation of measured values have shown to be quite effective.The distance, together with the computed direction, elevation, and azimuth, were inputs needed by the chosen BPNN model. We show and explain the experimental data and outcomes of configuring the BPNN model. An increase in the hidden layer neuron count results in a drop in BPNN model error when tested on training data. In this 3D situation, BPNN achieves a 97.5% success rate with a 95.29 percent validation rate and a 93.73 percent accuracy rate.Using a back propagation neural network for localization with PSO yielded the best results across all hybrid combinations examined. The simulation results showed that PSO-BPNN with tetrahedron 3D produced the highest Constance values of all the approaches tested. Inaccuracy measuring an average of 2.72 cm is quite considerable. The optimization procedure reduces the minimum localization error to 2.72 cm, which is notable compared to reference [UWB Localization System for Indoor Applications: Concept, Realization and Analysis", by Lukasz Zwirello], where it is 9 cm.

The work highlights the impressive accuracy achieved by ELPSO and PSO-BPNN in UWB localization, evidenced by the consistently low average localization errors across various movement positions. However, a crucial aspect missing for real-time applications is the consideration of computational efficiency. The absence of processing time and energy consumption data makes it challenging to ascertain the algorithms' feasibility in scenarios demanding immediate location updates, such as tracking moving objects or emergency response. Given the inherent complexity of these algorithms and the significant transmission range of 100 meters, potential challenges in real-time performance, scalability, and energy consumption arise. To bridge this gap, future evaluations must incorporate detailed measurements of processing time and energy usage, enabling a comprehensive assessment of the algorithms' suitability for practical, real-time WSN deployments.

The statistical mean localization error for each algorithm variation was calculated to assess their average performance across the four movement positions. For ELPSO-T, the mean localization error was found to be 1.535 cm, indicating a relatively low average error for this technique. ELPSO-LS exhibited a slightly higher mean localization error of 1.7375 cm. PSO-BPNN-T demonstrated the lowest mean localization error among the four, at 1.4525 cm, suggesting it achieved the highest average accuracy. Finally, PSO-BPNN-LS had a mean localization error of 1.625 cm. Compared with state of art the experiment work done by Zhuo etal. in 2023 about UWB localization with CNN-SVM hybrid algorithm with 4 anchor nodes stated that the validity and accuracy of the C-T-CNN-SVM algorithm are proved through a comparison with traditional and state-of-the-art methods. (i) Focusing on four main prediction errors (range measurements, maxNoise, stdNoise), the standard deviation decreases from 13.65 cm to 4.35 cm which is higher than our mean. (ii) After target positioning, the proposed method can realize a one-dimensional *X*-axis and *Y*-axis accuracy within 175 mm, and a *Z*-axis accuracy within 200 mm; a 2D (X,Y) accuracy within 200 mm; and a 3D accuracy within 200 mm, most of which fall within (100 mm, 100 mm, 100 mm). (iii) Compared with the traditional algorithms, the proposed C-T-CNN-SVM algorithm performs better in location accuracy, cumulative error probability (CDF), and root-mean-square difference (RMSE): the 1D, 2D, and 3D accuracy of the proposed method is 2.5 times that of the traditional methods. When the location error is less than 10 cm, the CDF of the proposed algorithm only reaches a value of 0.17; when the positioning error reaches 30 cm, only the CDF of the proposed algorithm remains in an acceptable range. The RMSE of the proposed algorithm remains ideal when the distance error is greater than 30 cm.

CHAPTER-IV

A Range free error control model using UWB for estimation of optimal node location in Homogeneous dynamic WSN with various soft computing approaches

4.0 Introduction

In this chapter, range-free localization with UWB is implemented with different DV-Hop techniques. This work describes the complete process of UWB signal processing from its acquisition, filtering methods, and obtained results, to determining the node location. This work examines the possibility of using modified localization algorithms for determining the anchor's location. This includes trilateral, nonlinear programming methods, and a geometric algorithm proposed by us. The work proposes a DV-HOP hybridization technique and optimal algorithms to decrease range-free settings' node localization errors. A 20mx20m area was selected for the present localization and anchors were placed at equal distances with square geometry. A distance of 20mts between the anchors was fixed and the outer range will be 10mts each from the anchor node. For the present research, a real-time open stadium was assumed to be the target nodes for locating the players. A sample size of 30 target nodes was considered for localization using extended DV-HOP techniques.

The novelty and the proposed work are as follows:

- CC-DV HOP, Hybrid DV HOP and Online sequential DV HOP (proposed) for node localization. From the above, DV-HOP techniques were used to identify node locations using range based least square (2D).
- To improve DV-HOP for this investigation, we used 3D measuring techniques and a sequential algorithm.
- The obtained results were compared with BBO, HPSO and FA algorithm results taken from the literature review.

The adoption of CC-DV-Hop (Corrected Communication DV-Hop) within range-free localization strategies, especially in UWB-enhanced WSNs, is primarily driven by the need to rectify the inherent inaccuracies stemming from the standard DV-Hop algorithm's simplifying assumptions. The original DV-Hop, relying on uniform hop sizes and prone to accumulating hop count errors, often yields suboptimal localization accuracy, particularly in irregular network topologies and environments with varying communication ranges. CC-DV-Hop, by introducing correction factors based on observed communication patterns and network topology, aims to refine the average hop size estimation. This refinement leads to more accurate distance estimations, thereby improving the overall localization precision. Even in UWB-based systems, where precise range measurements are theoretically attainable, the use of CC-DV-Hop presents a cost-effective and computationally less demanding alternative when direct range measurements are either unreliable due to environmental factors or excessively burdensome for resource-constrained nodes.

Hybrid DV-Hop strategies are employed to leverage the complementary strengths of range-free and range-based (or angle-based) localization techniques, effectively mitigating the individual limitations of each approach. The hybrid approach combines the coarse localization capabilities of DV-Hop with the precision offered by other methods, such as angle of arrival (AOA) or received signal strength indicator (RSSI), or even optimization algorithms. This integration allows for a two-tiered localization process, where DV-Hop provides an initial, approximate location, subsequently refined by the more accurate range or angle-based measurements. In UWB-based WSNs, this translates to utilizing the hop count information from DV-Hop in conjunction with the high-precision angle or time measurements afforded by UWB transceivers, achieving a desirable balance between accuracy and computational cost. This hybrid approach is particularly advantageous in heterogeneous environments where some nodes possess UWB range measurement capabilities while others rely on less precise, range-free methods.

Sequential DV-Hop is implemented to address the issue of error propagation that plagues the standard DV-Hop algorithm, especially in large-scale WSN deployments. By employing a sequential localization process, where node positions are estimated step-by-step using previously localized nodes as reference points, this method effectively curtails the accumulation of errors. This sequential approach ensures that errors introduced in earlier localization steps do not propagate and amplify in subsequent estimations, leading to a more accurate and consistent localization result across the entire network. In UWB-based WSNs, even with the inherent precision of UWB, sequential DV-Hop proves beneficial in minimizing the impact of hop count errors, particularly in extensive networks where such errors can significantly degrade localization accuracy. Furthermore, in scenarios where certain nodes lack UWB transceivers, this method provides a viable alternative for localizing these nodes within the network.

4.1 RANGE -FREE LOCALIZATION

WSN is low-cost, has high self-organization, can be quickly deployed, and is appropriate for a variety of applications, including monitoring targets, identification, and location. The current situation calls for the evaluation of improved methodologies and optimal techniques as range-free localization with UWB research advances. With the advancement of technology, more efficient methods and techniques have to be developed in order to improve the accuracy and reliability of range-free localization with UWB. This can help in reducing the complexity and cost of the system while providing better performance. When it comes to single localization zones, the focus is on accuracy. DV-Hop is low in cost and does not require any additional hardware to be implemented. As a result, many applications can benefit from DV-Hop. The DV-Hop algorithm still gives rise to significant localization mistakes. In order to lessen the impact of localization errors, this study applied the DV-Hop algorithm with the Particle Swarm Optimization method. The research proposes a better DV-Hop location algorithm that incorporates different communication radii to address the issues with DV-Hop location algorithms' handling of node density. With the updated DV-Hop locating method, the average positioning error of the unknown nodes is reduced and positioning accuracy is enhanced.

The DV-Hop algorithm's positioning accuracy and performance have been significantly enhanced thanks to the extensive research on the algorithm by numerous researchers who have offered various improved techniques to address the algorithm's problems. The DV-Hop algorithm determines the location of the unknown node by averaging the hop distances from the closest beacon node. It improves positioning accuracy, but as the transmission radius grows, so does the network the cost.

4.1.1 Principle of DV-Hop algorithm

Current DV-Hop algorithms often operate under the assumption that node-to-node connections are linear, whereas in reality, such paths are more often than not curved. The monitoring area is equipped with sensor nodes that were randomly seeded. Additionally, every beacon node transmits packets to the network, which include the location and hop value of the beacon node. By adding one to the hop value at each intermediate hop. When determining the unknown node's position, a matching positioning approach takes into account the estimated distance between each beacon node and the unknown node. As seen in Figure 1, the distribution of nodes in the network is not uniform. Given that the distance between anchor nodes is significantly larger than that between unknown nodes, the DV-Hop algorithm incorrectly determines the average hop distance as one hop.

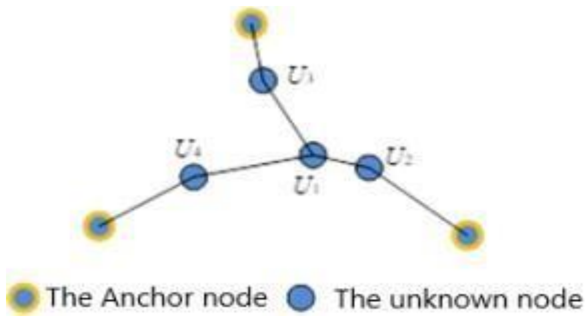


Figure 4.1: Uneven distribution of unknown nodes in range free environment

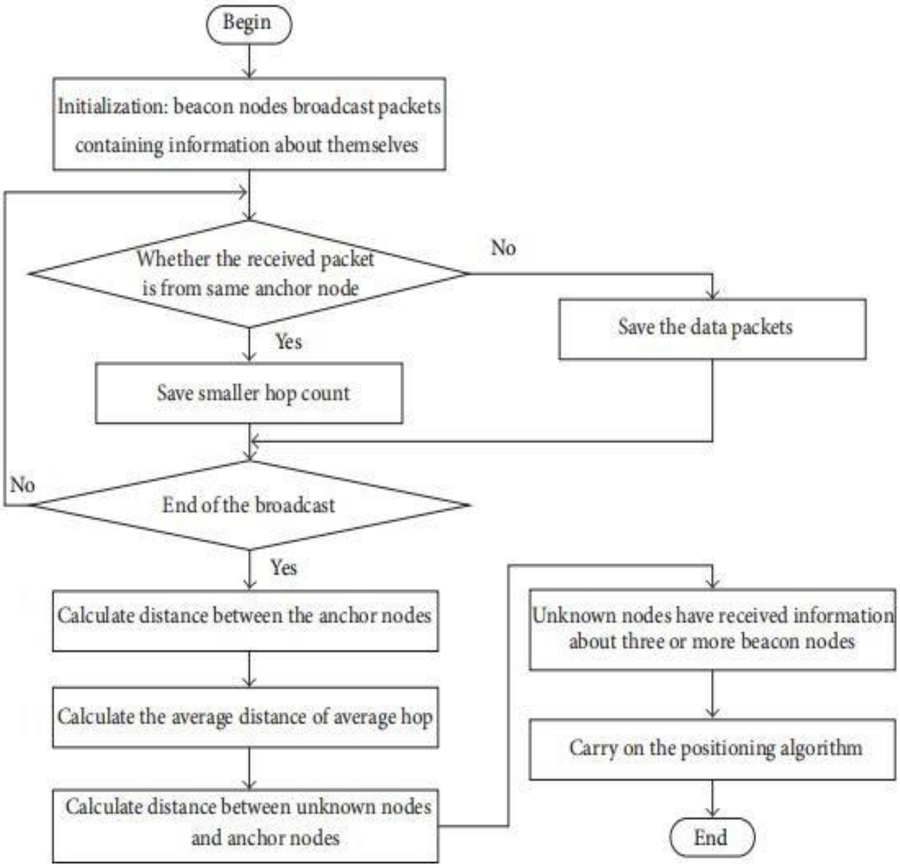


Figure 4.2 Conventional DV-Hop flow chart

4.1.2 Measurement with DV-Hop

Traditional DV-Hop positioning algorithm divided in to three phases

1) Minimum hops for each beacon from unknown nodes and compute nodes. 2 ） Finding the accurate hop distance between the unknown node and the beacon node. 3 ） Determining its own location with the use of the trilateration approach detection or the maximum likelihood estimate technique.

In order to inform their neighbours of their whereabouts, beacon nodes transmit data packets with the hop number field set to 0. Bypassing a beacon node with an excessively high hop count in a packet and instead receiving node records from all beacon nodes with a minimum hop count. Hop up to the next neighbour and go further by one. Using this technique, any node in the network can capture data from every beacon node with a hop count that is below the minimum required. In the first phase, every beacon node keeps track of its own position and the distances travelled by hops; then, using equation (1), it estimates the average distance travelled by hops.

2) Determine the average hop distance between the nodes and get it. Using equation (1), beacon nodes can save each other's coordinates and determine the least number of hops. Determine the average distance between nodes in the network:

$$HopSize_i = \frac{\sum_{i \neq j}^{n} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sum_{i \neq j}^{n} h_{ij}} \qquad (1)$$

The beacon coordinates of nodes i and j are (xi, yi) and (xj, yj), respectively. The minimal number of hops between these two nodes is hop(ij). After that, the network's beacon node will determine the average distance per hop using a packet's lifetime of broadcasting; the unknown node will only receive the first average distance per leap and then relay that information to its neighbours. The average distance per hop is communicated to the most recent beacon node from the node using this approach. The standard hop distance is sent to the unknown node based on the recorded

calculate the hop distance for each beacon node. In the second stage, the unknown node determines its coordinates by recording the distance jumps from each beacon node using either the maximum likelihood estimation approach or trilateration measurement. To find out how far away the unknown node u is from the anchor node i, we can use the formula di,u.using the next formula:

$$di,u = hi,u \times HopSizei \ldots\ldots(2)$$

Then for the trilateration method the distance separation from anchor nodes to unknown nodes can compute the position using

$$\begin{cases} (x_u - x_1)^2 + (y_u - y_1)^2 = d_{1,u}^2 \\ (x_u - x_2)^2 + (y_u - y_2)^2 = d_{2,u}^2 \\ . \\ . \\ . \\ (x_u - x_n)^2 + (y_u - y_n)^2 = d_{n,u}^2 \end{cases} \quad (3)$$

From the above equation where the unknown node position is (x_u, y_u) and the anchor position is (x_n, y_n) the equation can be written as

$$Ax=B\ldots(4)$$

Finally, the least square method aims to solve equation (4), as follows, and determines the coordinates of unknown nodes in the network.

$$X= (A^TA)^{-1}A^TB\ldots..(5)$$

Then we get x=X(1) and y=X(2)

4.1.3 DV-Hop measurement with least square

The distance matrix d*n* is dimension between anchor and the node is calculated using the following equations:

$$\sqrt{(x-x_i)^2 + (y-y_i)^2} - d_i| \leq \varepsilon_i, \text{ i= 1, 2, 3….. n} \qquad (6)$$

Expansion refers to the identification equations:7,8,9

$$d_1 - \varepsilon_1 \leq \sqrt{(x-x_1)^2 + (y-y_1)^2} \leq d_1 + \varepsilon_1 \quad (7)$$

$$d_2 - \varepsilon_2 \leq \sqrt{(x-x_2)^2 + (y-y_2)^2} \leq d_2 + \varepsilon_2 \quad (8)$$

The final formula can be written as

$$d_n - \varepsilon_n \leq \sqrt{(x-x_n)^2 + (y-y_n)^2} \leq \mathrm{dn} + \varepsilon_n \ (9)$$

The objective of our strategy is to solve the least square problem using Regularized Least Squares (RLS) and then utilise regularization to further limit the solution. We enhance the solution based on equality constraint and generalization performance for anisotropic WSN by taking into account the mistake generated by inter-nodes distances estimate. Reducing the vector norm and quadratic localization errors is the fundamental goal of this method. The following goal function provides a description of the suggested method:

$$\Omega = \arg_{\Omega}\bullet \min\|Hca\times\Omega - Da\|^2 + \alpha\|\square\Omega\|^2 \quad (10)$$

The distance estimation Dn between anchors and unknown nodes can be represented in the following way, after the hop-count matrix Hcn with dimensions nn × na is known and demonstrated for the unknown sensor nodes and anchor nodes:

$$Dn = Hcn\cdot\Omega\bullet = Hcn(Hca^{T}Hca + I/C)^{-1}Hca \cdot Da \quad (11)$$

The precise position of the anchor nodes matrix (with dimensions na × 2) is observed by Xa. Xu takes note of the estimated unknown geographical position of the sensor nodes matrix, which has dimensions nn × 2. What follows is an assumed linear equation representing the relationship between the geographical position matrix Xa and the network distances Da: $Da\ .\Psi = Xa$ (12)

Table: 4.1Minimum HOP count between anchors

	A1	A2	A3	A4
A1	0	4	4	4
A2	4	0	4	4
A3	4	4	0	4
A4	4	4	4	0

The least squares solution given by the formula

$$\Psi = Da^{+}\ .Xa\ldots\quad (13)$$

$$\text{Then } Da^{+} = (Da^{T}Da)^{-1}Da\ \ldots\ldots (14)$$

The position of unknown sensor node can be given as

$$Xu = Dn\ .\Psi = Dn.\ (Da^{T}Da)^{-1}Da.\ Xa\ldots (15)$$

This is a calculation example that demonstrates the suggested method. An A-list of known nodes (UN included) and some unknown nodes (A1, A2, A3, and A4) make up the proposed sensor network. In this diagram, the red and blue nodes stand for the same thing. The depicted sensing area in Figure 4.3 is 20 m × 20 m. Roughly ten metres is the range that each node may connect to. When an anchor uses a GPS module, it may track not only its position in the network but also its distance and hop count, which are represented in Table 1 as Da and Hca, respectively.

Table: 4.2 Real distance between anchors (meters)

	A1	A2	A3	A4
A1	20	20	20	28.28
A2	20	20	28.28	20
A3	20	28.28	20	20
A4	28.28	20	20	20

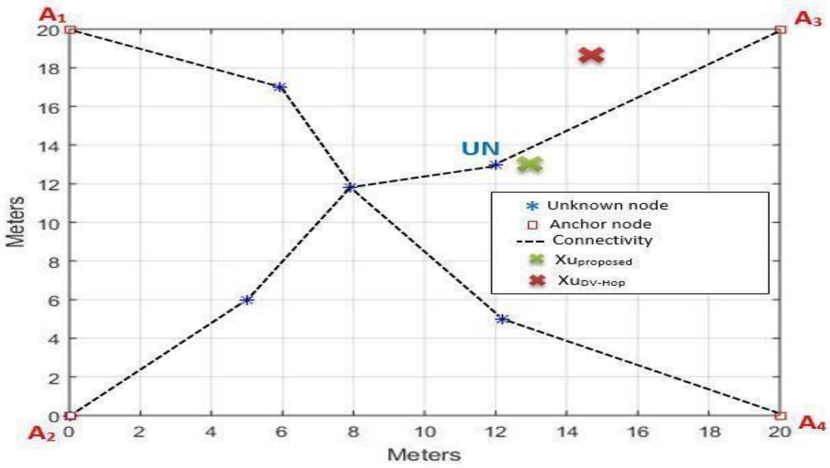


Figure 4.3 Network localization area in range free environment

Table 4.3 Estimation of matrix size for given area

Ω	A1	A2	A3	A4
A1	5.6	0.74	0.74	-1.4
A2	0.74	5.6	-1.4	0.74
A3	0.74	-1.4	5.6	0.74
A4	-1.4	0.74	0.74	5.6

4.1.4 Measurement with 3D- method for Dv-hop

Based on the locations of the LAs and the distances obtained, one can deduce the location of a sensor. In this case, the state variable is the location of a sensor node in a three-dimensional model. The state of the it sensor node following the nth cycle is:

$x_i(\mathrm{n}) = \{x_{i1}(\mathrm{n}), x_{i2}(\mathrm{n}), x_{i3}(\mathrm{n})\}$..............................(16)

In addition to following equations for the dynamic state and assumptions:

$x_i(\mathrm{n}) = \mathrm{f}\big(x_i(\mathrm{n}\hat{\mathrm{a}}^{\hat{}\,\prime}1)\big) + w_i(\mathrm{n})$, ... (17)

$y_i(\mathrm{n}) = \mathrm{g}\big(x_i(\mathrm{n})\big) + V_i(\mathrm{n})$... (18)

One possibility is static sensor localization, where the sensors stay still after deployment. There is no other function than similarity that governs the dynamics of the sensor position state f(x):

$x_i(\mathrm{n}+1) = x_i(\mathrm{n}) + w_i(\mathrm{n})$ ....(19)

Using RF signalling, we can communicate our present position to the sensors, and we can also predict the little amount of positional disturbance caused by wind and other environmental factors. Applying this research framework:

$y_i(n) = \sqrt{(\hat{\mathrm{a}}^{\hat{}}\dagger\, x_{i1}(n))^2 + (\hat{\mathrm{a}}^{\hat{}}\dagger\, x_{i2}(n))^2 + (\hat{\mathrm{a}}^{\hat{}}\dagger\, x_{i3}(n))^2} + v_i(n)$………… (20)

Here Δxi1(n) = xb 1(n) − xi1(n), Δxi2(n) = xb 2(n) − xi2(n), Δxi3(n) = xb 3(n) − xi3(n); and (xb 1(n), xb 2(n), xb 3(n)) is the current 3D position of the LA (least arthematic).

4.1.5 Equations with fitness functions

The relationship between the prediction localization accuracy and the value of f (x, y) in Equation (2) changes as the number of errors ε1, ε2, ε3. εn decreases. Resolving the estimated coordinate (x, y) (2) can transform the location problem into a nonlinear minimum value problem, which will lower the value of f (x, y) in Equation 1. When analysing and controlling the particle's research path, the algorithm makes use of the fitness function. Something like this is called a "fitness function."

$f(\mathrm{x,y}) = \frac{1}{N}\hat{\mathrm{a}}_{i=1}^{N} | \sqrt{(x\hat{\mathrm{a}}^{\hat{}\,\prime}x_i)^2 + (y\hat{\mathrm{a}}^{\hat{}\,\prime}y_i)^2 \hat{a}d_i} |$ (21)

(xi,yi) is the position coordinate of beacon node I f(x, y) is the particle's fitness value, and did is the distance between an unknown node and beacon node i.

4.1.6 Co-ordinate Correction DV-Hop method

Despite the fact that an improved distance vector-Hop localization algorithm (CC-DV- Hop), which exploits the coordinate correction. In fact, the coordinate correction via the DV-Hop gives the pseudo-range error coefficient which improves the length of the average distance per hop. Moreover, the unknown node and the anchor nodes are considered as unknown when obtaining their coordinate correction values which are employed to correct iteratively the localization results of unknown nodes. In the distance vector exchanging stage for the traditional DV-Hop algorithm, as long as the distance between the beacon node and the unknown node is less than the communication radius R, the hop number is recorded as 1. This means that there may be a large actual distance difference between two groups of unknown nodes with the hop number of 1 and beacon nodes. As shown in Fig. 3, there are some unknown nodes B and C around beacon node A, and the hop value of the unknown node and beacon node is also 1, but the actual distance between the two unknown nodes and beacon node is very different. Generally taking the hop value between them and the beacon node as 1 will reduce the positioning accuracy of the DV-Hop positioning algorithm and the stability of the algorithm. When communicating vector distances between the beacon and unknown nodes, a standard DV-Hop algorithm considers distances lower than R.the hop values of anchor nodes and beacons are equal, the actual distances between them are significantly different. Applying CC DV-Hop techniques with two communication channels will greatly enhance the effectiveness of this problem solution. Three anchor nodes are necessary for archive node positioning. Among other things, the four anchors should correct each other and announce the actual distance.

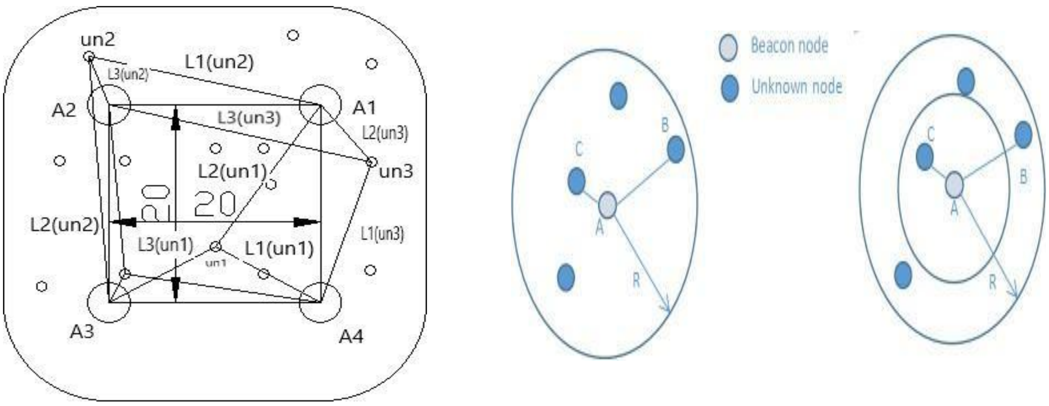


Figure:4.4 Node localization with minimum three anchor distance with correction in a selected environment

Assume that four anchor nodes having outer range sensing of 10mts of location tracking as shown in figure 4.4, conventional method of unknown node falling in the area of 3 anchors the regular radial distance calculated with least squares. The coordinate (x1, y1) , (x2,y2) and (x3,y3) for un1, the distance measured from A1,A4, A3 respectively.

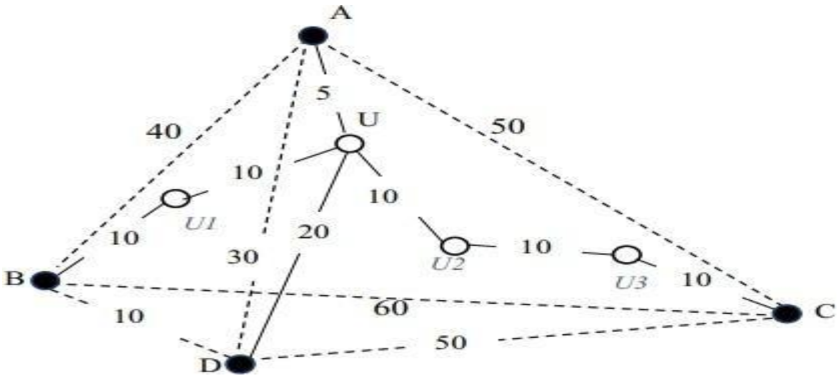


Figure: 4.5 Anchor placements in 3D within communication range

The 3D position of the unknown node U in a realistic setting, with anchor nodes A, B, C, and D placed accordingly. Our previous statement about the maximum communication range for each anchor was 30 metres. In this case, the distances between the anchor nodes are as follows: 40 between A and B, 30 between A and D, 50 between C and D, 10 between B and D, and 60 between B and C. It takes one hop for U to reach A, two for U to reach B, three for U to reach C, and one for U to reach D. Assume, in the worst-case scenario, that the unknown node U is 5 nodes away from A, 20 nodes away from D, and that the hop size for the remaining hops is 10. This is how the DV-Hop algorithm determines the hopsize of anchor nodes A, B, C, and D:

A: (40+50+30)/(3+4+2) = 13.33

B: (40+60+10)/(3+5+3) = 10

C: (60+50+50)/(5+4+4) = 12.30

D: (10+30+50)/(2+3+4) = 10

The hop sizes of anchor nodes A, B, C, and D will be broadcasted in the following order: 13.33, 10, 12.30, and 10, respectively. When either A or D send a message, the first node to receive it is the unknown U. The process continues by determining the distances between each node: 13.33 between itself and anchor node A, 26.66 between U and B, 53.32 between U and C, and 13.33 between U and D. The true separation between the anchor node and the stranger node U. The improved DV-Hop algorithm based on double communication radius with co-ordinate correction proposed in this updates the minimum hop number obtained by the unknown node which is closer to the beacon node to a smaller hop number by adding a communication radius and keeps the minimum hop number information of the unknown node which is far away from the beacon node at the same time. It shows the difference of the actual distance in terms of the hop number, which solves the problem of the large difference between the actual distances of the same hops to a certain extent, and then is helpful to estimate the more accurate average jump distance.

Algorithm 9 :Improved DV-Hop with Co-ordinate Correction (2D)
Input: Mobility of Unknown node
Out put: Number of anchor nodes (at least 3) communication unknown node
1. Initialization WSN 2. Hops; hop count(an integer) 3. Anchor nodes: number of anchor nodes in communication (an integer)
4. Begin 5. for every unknown node u 6. for Hops=1:n 7. If (anchors≥ 3 communicate value) 8. Then 9. return Hops 10. end if 11. Else increment Hops 12. end for 13. end for 14. return in sufficient anchors in radius.

Algorithm 10 :Improved DV-Hop with Co-ordinate Correction (3D)
Input: Mobility of Unknown node
Output: Number of anchor nodes (at least 4) communication unknown node
1. Initialization WSN 2. Hops; hop count(an integer) 3. Anchor nodes: number of anchor nodes in communication (an integer)

4. Begin
5. for every unknown node u
6. for Hops=1:n
7. If (anchors≥ 4 communicate value)
8. Then return Hops
9. end if
11. Else increment Hops
12. end for
13. end for
14. return in sufficient anchors in radius.

The minimum hop number for the unknown node is kept constant, but diminished, when a communication radius is added. Discordance between the real distance between subsequent hops is eradicated as a result of using the hop number to calculate distance. To grasp the general average jump, one must have knowledge. Exploring and evaluating models and outcomes. The enhanced method was evaluated using a dual communication radius. Here, we use MATLAB to model the CC DV-Hop method, improve the DV-Hop algorithm, and evaluate alternative algorithms with four anchor nodes and varying communication radii and beacon proportions. Furthermore, the efficiency of the suggested approach is evaluated using root mean square error (RMSE). We ran a simulation to find the root-mean-squared error (RMSE) for different values of the following parameters: total nodes, anchor node percentage, and communication radius of sensor nodes.

$$RMSE = \sqrt{\frac{1}{t}\sum_{i=1}^{t}\left[(x_i^u - x_i^a)^2 + (y_i^u - y_i^a)^2 + (z_i^u - z_i^a)^2\right]} \quad ...(22)$$

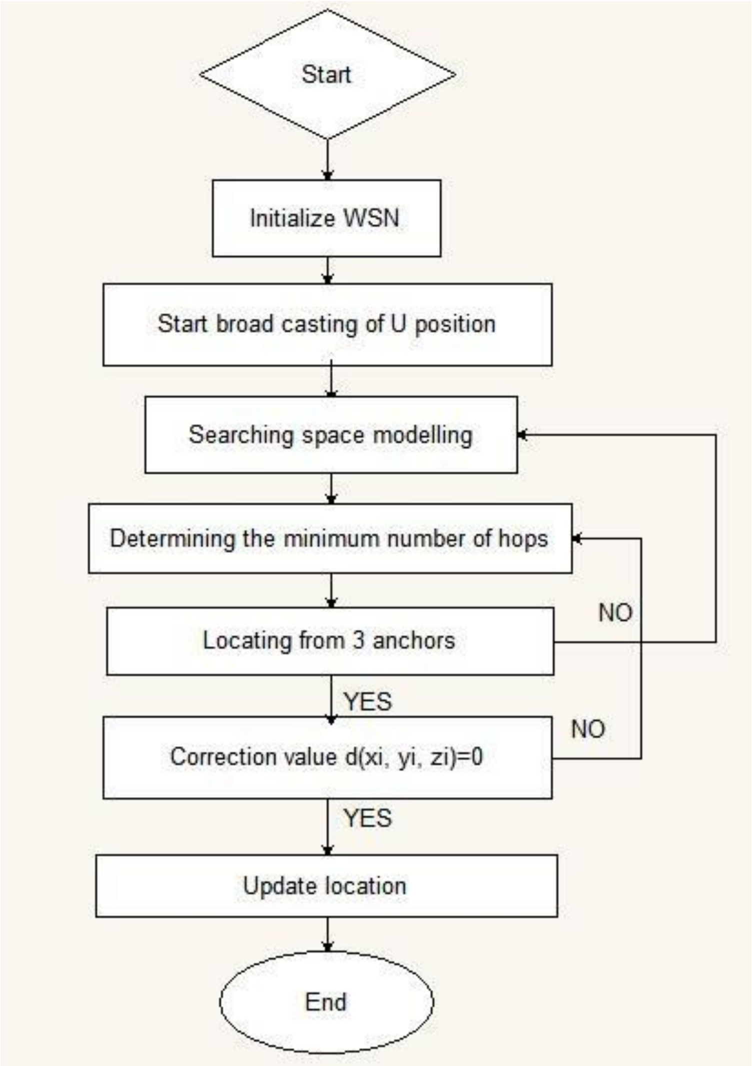


Figure 4.6 Flow chart for CC DV-Hop

When compared to single transmission radii, minimal hop distances between nodes offer superior accuracy. The CC DV-Hop method employs a doubled communication radius to keep track of the hop count for the unknown node further away, while minimising it for reference nodes close to the beacon node. When characterising the intervals between neighbouring frames, it is now easier to compute an average jump distance using hop characteristics. For this reason, CC DV-Hop can't function at peak efficiency without a longer communication range.

4.2 HYBRID DV HOP MODEL

The research further continued with hybridizing the DV-Hop algorithm with differential estimation controlled from CC DV-Hop communication radius of anchor nodes.an updated differential estimation algorithm checked for the present real time scenario to improve location accuracy with hybrid method. The differential evolution (DE) algorithm maintains the population-based global search strategy in evolutionary computing and updates the population using actual coding. A one-to-one elimination mechanism and a straightforward difference-based mutation operation simplify the operation of the genetic algorithm. Finding additional nodes in a network becomes much easier when immediate neighbours are used as anchors. Once a sensor node is found, each sensor is linked to an anchor. More "converted" anchors can be added to the geometry process to make localization even more accurate. A study found that a node's localization was more accurate the closer it was to an anchor. Before placing those that are further away from anchors, place those that are closest to them first. Flooding occurs in the first phase, distance per hop is calculated in the second, and sensor location is determined in the third phase. Algorithms outline the various processes that are part of phases 1 and 2, which anchor nodes perform, and phase 3, which sensor nodes perform. The anchors then start finding unknown nodes. The pedestrian detection process is started by sending a Los Start Msg message to each anchor. In the Los Start message, the Start Msg field is most prominent. Anchor nodes are those with nodal IDs; nodes without them are those that do not have them. A node with a non-anchor type is one that lacks an anchor ID. Coordinates of nodes, which are real for anchor nodes but approximations for other sensors, need to be made to match. Every node that gets this message first finds out where it is, and then it sends it on to its neighbours just around the corner. Once we accomplish this, we can guarantee that localization starts and continues at the anchor node. Each node that gets this message keeps a record of the other nodes network identifier and a rough position in its memory. If a node has three or more neighbours or anchors, it can utilise triangulation to know where it is. At the top of a node's Loc Table, you can see all of its reachable anchors, along with their coordinates and hop size. This data is obtained in phases 1 and 2.

4.2.1 Hybrid DV hop flow chart

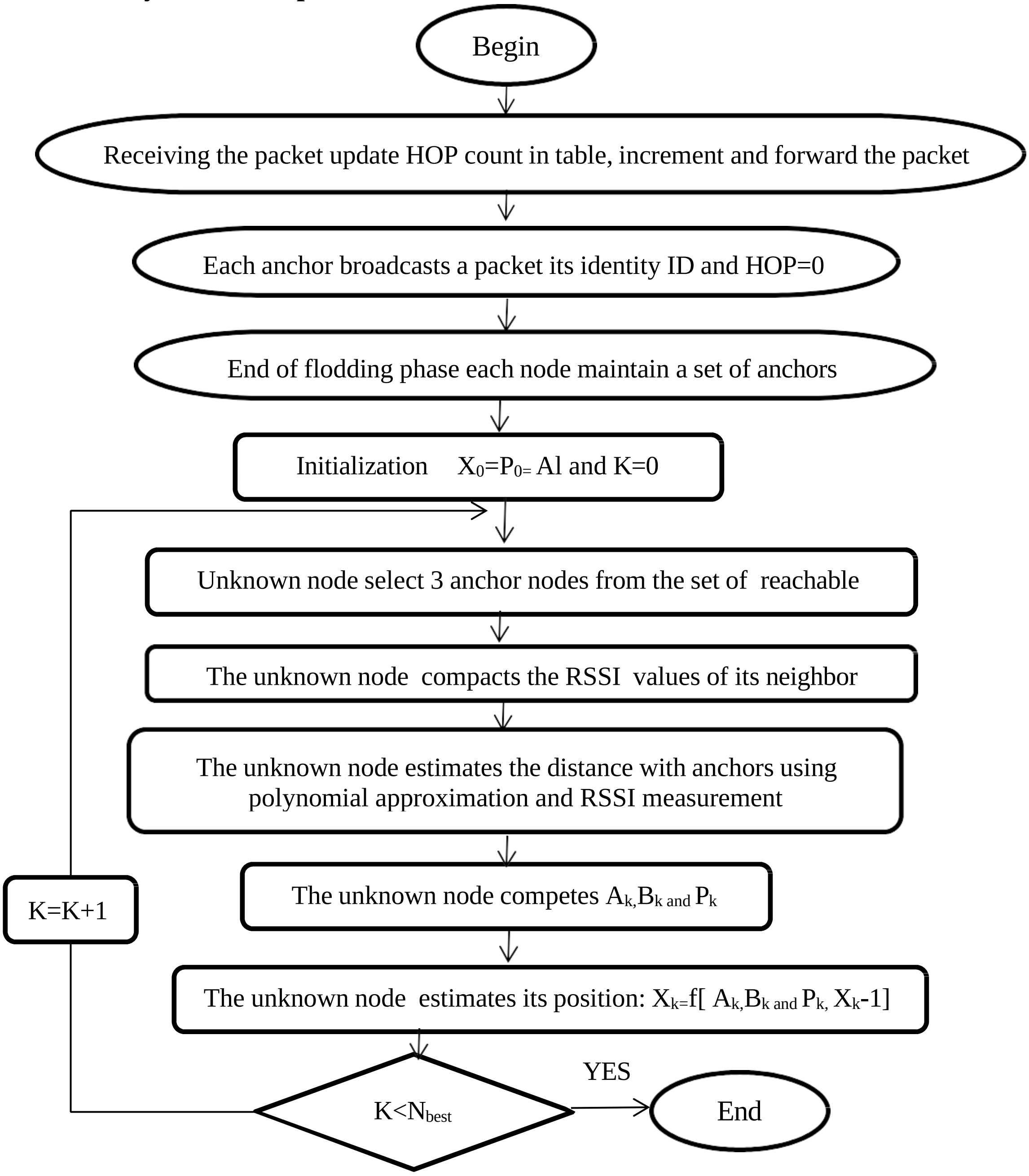


Figure:4.7 Hybrid DV Hop flow chart for positioning.

Figure 4.7 shows the flow diagram for the two steps of node deployment and localization using four anchor nodes. If the distances between the nodes are accurately measured, the localization phase loop will recalculate their locations.

	Algorithm 11: Hybrid DV- HOP algorithm
Input	List of reachable Anchors $\{A_i, 1 \leq i \leq n\}$, with their coordinates and Hop size
Output	Unknown node (N) position estimation
	For each anchor $A_i, 1 \leq i \leq n$ do
	If A_i is neighbor to un known node (N) (HOP Count==1), then
	To estimate distance to A_i(%use RSSI)
	Distance N, A_i = get Distance (RSSI $_N$, A_i)
	Else/
	% Use of Hop size A_i (To estimate distance to A_i)
	Distance N, A_i = Hop size A_i* HOP(i)
	End if
	End for
	If received (Loc)* message then
	Node ID and node Coordinate addition to Loc Table
	N_bAnchor = number of one-hop anchors (hot Count =1)
	If N_bAnchor>=3 then
	Estimated positionN=Triangulation ($A_i, 1 < i < N_b$Anchor)
	Else/
	N_b(Neig) = number of already localized neighbors
	{Neig($_I$),1< i < N_bNeig}=The set of already localized neighbors
	Use RSSI to estimate distance to Neig($_I$),$1 \leq i < N_b$Neig
	Estimated position N= Triangulation (A_i,1<i <Nb Anchor, Neig$_i$,1<i < N_bNeig)
	End if
	Communicate the estimated position of N to its neighbors
	End if

4.3 Proposed: Online sequential DV Hop localization algorithm

Determine the unknown nodes' locations by finding the largest distance one hop (or one-hop size) from each anchor. This distance estimate would be more useful if it were more precise. First, the DV-Hop algorithm determines the average hop distance between anchors; second, it discards the previous technique. In this way, we were able to calculate the average hop length. Consequently, it was recommended to use polynomial approximation in order to improve localization accuracy and decrease anticipated location error.

The number of sensor nodes varied between twenty and one hundred in the MAT lab simulation. Twenty metres was the maximum direction the signal could go. In designing the network, we made an effort to consider four separate alternatives: in other words, 10%, 20%, 30%, and 40% of all sensor nodes, respectively. Increasing the number of sensor nodes in a network lead to a decline in the accuracy of position estimates, as seen in Figure 4. Since there are more one-hop neighbours due to the increased density of sensor nodes, the triangulation function receives more data, leading to a more precise location estimate. A compute node will not produce any results with an anchor rate of 10% to 20% and a sensor node count of 10 to 20. Instead of using the Selective 3-Anchor technique, the hybrid DV-Hop strategy is required when anchor rates are low. At this valid point, there are fewer anchors to pick from. At 30% and 40% anchor levels, the Selective 3-Anchor system outperforms typical DV-Hop systems in terms of node density. At 60 nodes (or 50 nodes, respectively), the Selective 3-Anchor method begins to outperform the classic DV-Hop strategy with 30% and 40% anchor ratios, respectively. Determine the unknown nodes' locations by finding the largest distance one hop (or one-hop size) from each anchor. This distance estimate would be more useful if it were more precise.

The calculation of the average hop distance. Unidentified node locations are determined by averaging the hop distances estimated by each anchor in the network, which is one hop size from another anchor. If this calculated distance is quite specific, then the predicted placements will also be very accurate. A novel approach to determining the average hop distance across anchors is used in Step 2 of the DV-Hop algorithm as an alternative to the conventional method. Therefore, it was suggested to employ the polynomial approximation to enhance localization accuracy while minimizing the inaccuracy of predicted locations.

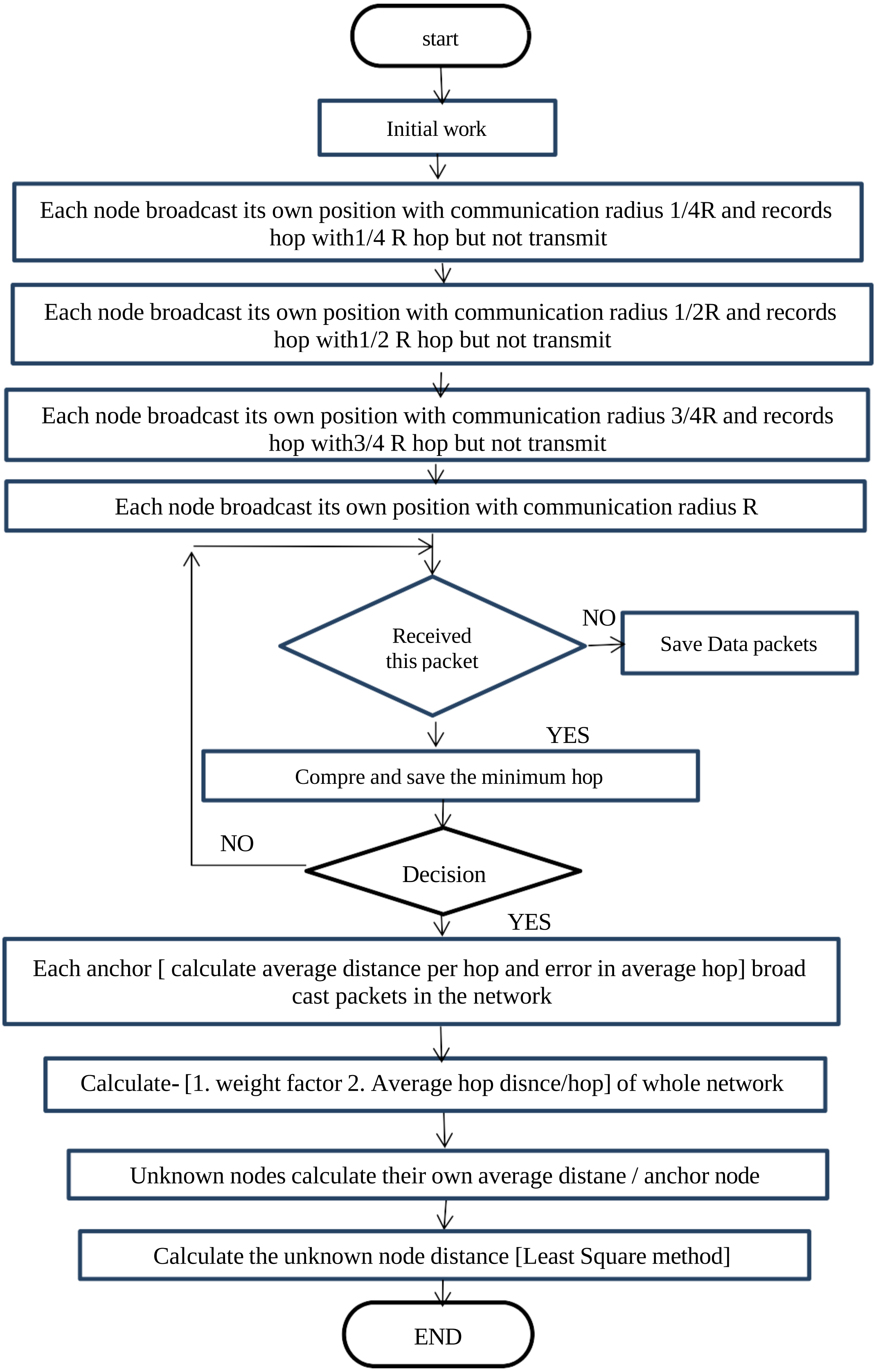


Figure 4.8: Flow chart for proposed Hybrid algorithm.

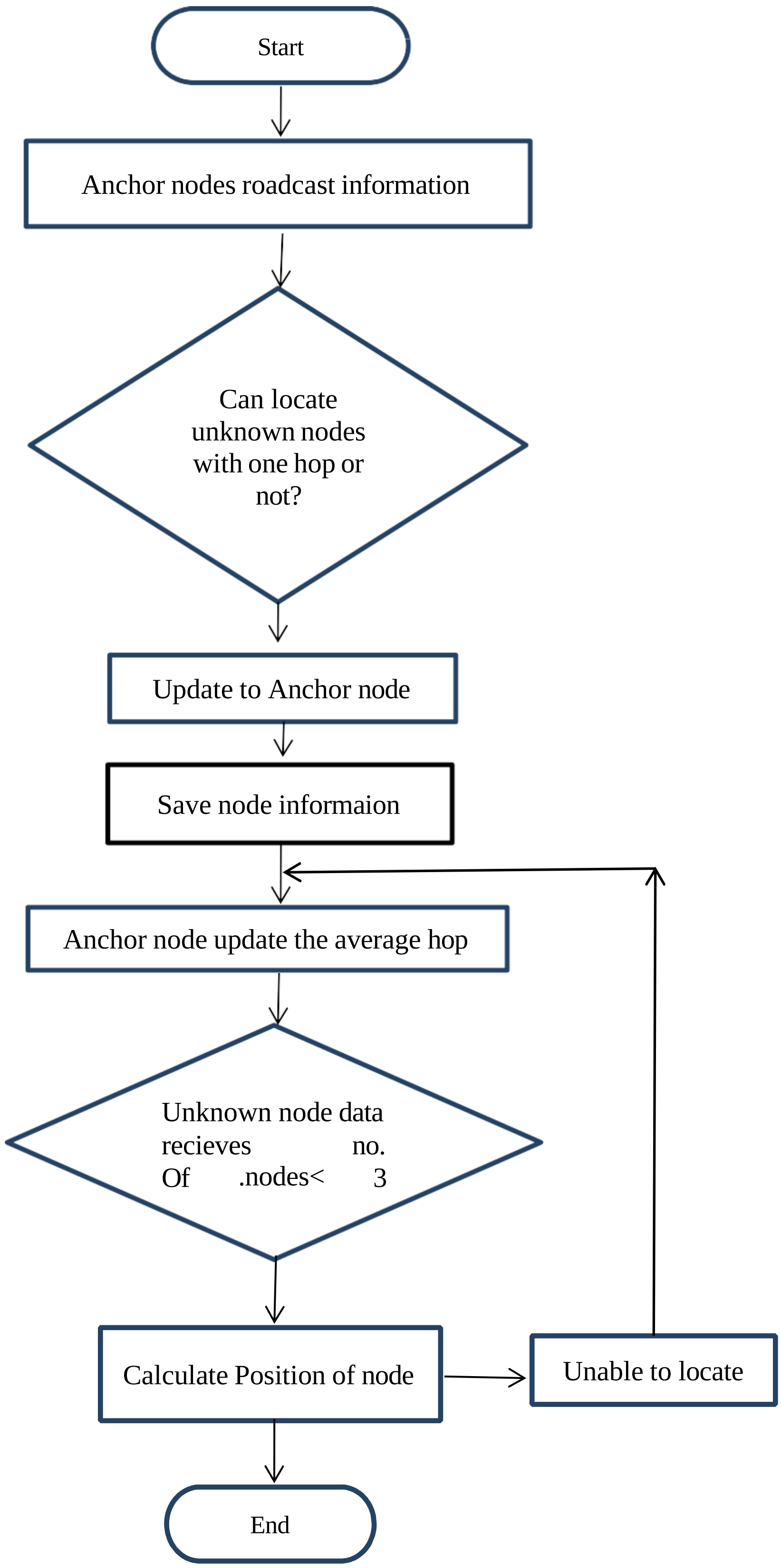


Figure: 4.9 Sequential flow chart of DV-HOP

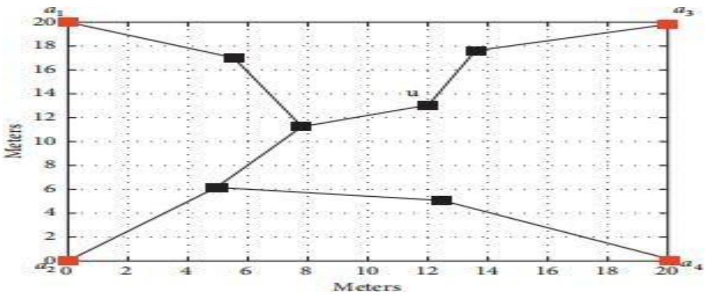


Figure 4.10 Flow chart and the HOP with anchor connectivity in range free localization.

	Algorithm 1 (seqential DV-HOP)
Input:	WSN: Coordinates (x_i,y_i) of Anchor nodes where i=1..Na,Na: Population size (Anchors);
Output:	Estimated position X_m of *m*= sensor nodes (unknown)
(1)	**Begin**/*Initialization
(2)	$X_{m(o)}$=0/ *initial position of unknown node to estimate
(3)	S=λ*i/*covariance matrix S, where 'i' is the identity matrix; λ is a very large positive number
(4)	Locate nodes that can be used as anchors in the position estimate process.
(5)	**While** (at least one of nodes is not localized) **Do**
5.1	Calculation of the smallest possible number of HOPs between a selection of anchors that are accessible for localization
5.2	To find the shortest path with the few HOPs, we can use the Least Squares method (LS) or a polynomial approximation
5.3	An algorithm 1 for determining the least number of hops between a given anchor and an unknown node.
5.4	Use the polynomial approximation to calculate the distance between anchors(i) and unknown nodes. (*j*): $d_{ij} = \propto_0 + \propto_1 h_{ij} + \propto_2 h_{ij}^2$
5.5	An approximation of the distance b between two unknown nodes can be calculated using polynomials to estimate their positions, Xm. Xk+1= Xk+ Sk+1AT k+1(Bk+1- Ak+1 Xk)
(6)	End while;
(7)	X_m/ *Estimated position of all unknown nodes m
(8)	End;

After polynomial calculation the error calculation done by using formula 11

$$err\_dis_j = [\sum_{i \neq j} |d_{true} - d_{eastimate} \mid ij/hosp_{ij}]/n_i \qquad (23)$$

In order to further improvement of localization accuracy the average distance of hop node I is defined as

$$c\_err\_dis = [\sum_{i \neq j} |d_{true} - dis_i \;/\; n \qquad (24)$$

The formulas 24 and 25 represent updates to the average distance across the network and the difference between the beacon nodes' actual distances.

$$new\_cc = cc + kXc\_err\_dis \qquad (25)$$

In this formula k is the variable parameters $-1<K<1$, the value of K changes the environment range, the new distance error is calculated by using the formula 26

$$d_i = new\_ccX\, hop_i \qquad (26)$$

To estimate upper and lower limit of network area the environment taken as

$$S\ area|x_{min} \leq x_{area} \leq x_{max}, y_{min} \leq y_{area} \leq y_{max},$$

The number of mistakes starts to get close to infinite as h gets closer to zero or hmax. We have noticed that the stability range of the new approach for ($\alpha 2 + 1$) is similar to the previous algorithm's, with $\alpha=0$, and is independent of environmental dynamics. The algorithm is initialized with X0 = 0 and S0 = λI,

where λ is an incredibly massive positive integer and I is the identity matrix. As the value of λ increases, the confidence in the original estimate of Xk declines. If you use a big λ, the RLS method will quickly deviate from the initialisation value of X0 = 0, which is akin to viewing the initial estimate of Xk as highly speculative.

The suggested DV-Hop approach uses online sequential computing to iteratively construct a set of nc candidate anchors for localisation. These anchors are randomly picked according to their availability in the population. The initial position of each other node (unknown node) is X0 =0

Finally, it calculates node positions using the DV-Hop method and the suggested average hop distance adjustment. An enhanced sequential formula is used to predict the location of an unknown node.In Algorithm, we offer the pseudocode for our localisation algorithm.

4.4 RESULTS AND DISCUSSIONS

These results primarily focus on performance analyses of DV-Hop and DV-Hop-based augmentation algorithms. All of the suggested solutions were evaluated for accuracy and localization flaws using the MATLAB simulator. Updates to the PSO algorithm have made it possible to pinpoint ultra-wideband (UWB) range-free wireless networks with increased accuracy. The number of anchor nodes changes from 10% to 20% and the wireless transmission distance changes from 20% to 50% between samples.

Table 4.4: The experiment was run ten times with uniformly distributed random node locations for each simulation.

No. Of Nodes	Anchor rate	Transmission range	Environment dimension
30	10% to 50%	Variable	100mtsx100mts
30	variable	Up to 50mts	100mtsx100mts

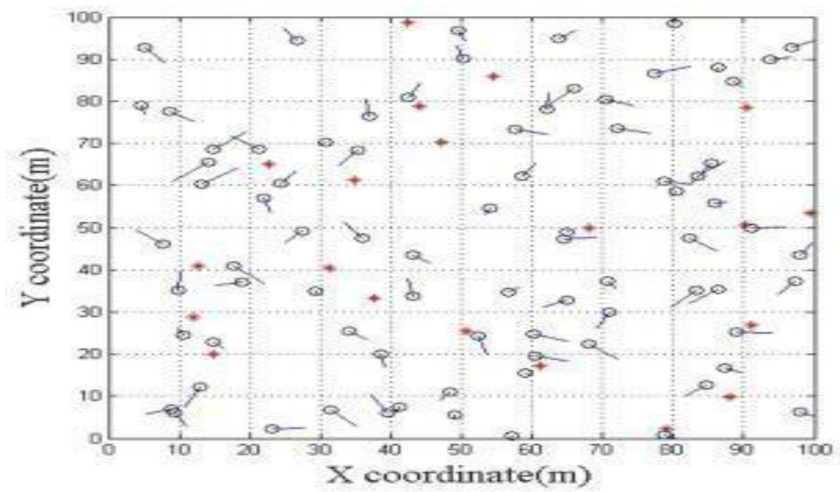


Figure 4.11: Node error distribution in selected range

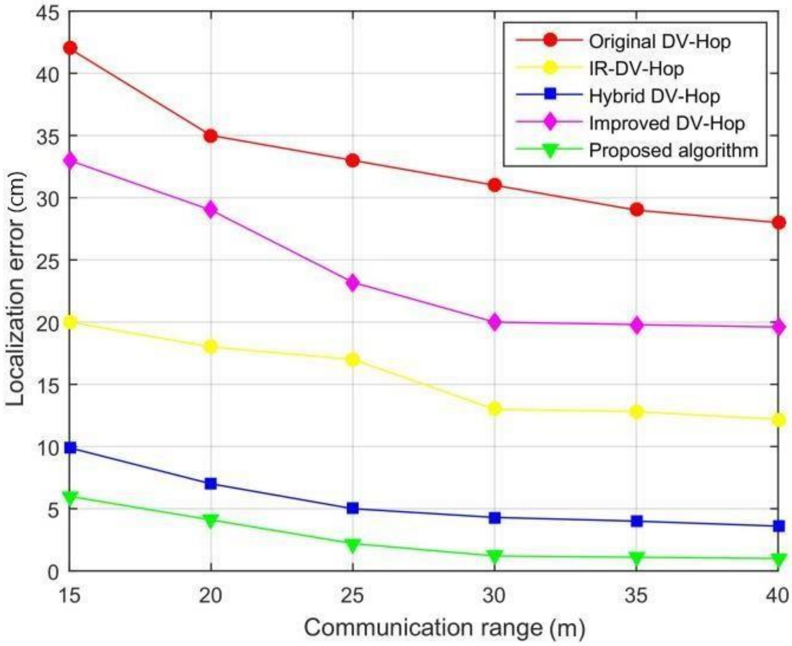


Figure: 4.12 localization error distribution in selected range

the distribution of node errors in the selected area, the error with conventional DV-HOP and Hybrid DV-HOP may be calculated, as shown in figure 4.15. Then, Figure 4.16 shows a comparison of the error with three anchor nodes. The results show that the localization procedures are more accurate than the anchor nodes.

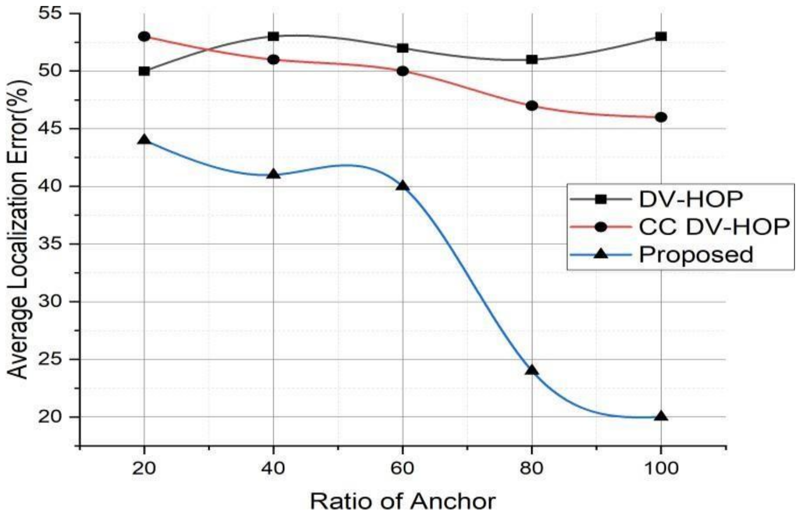


Figure:4.13 localization error vs ratio of anchor

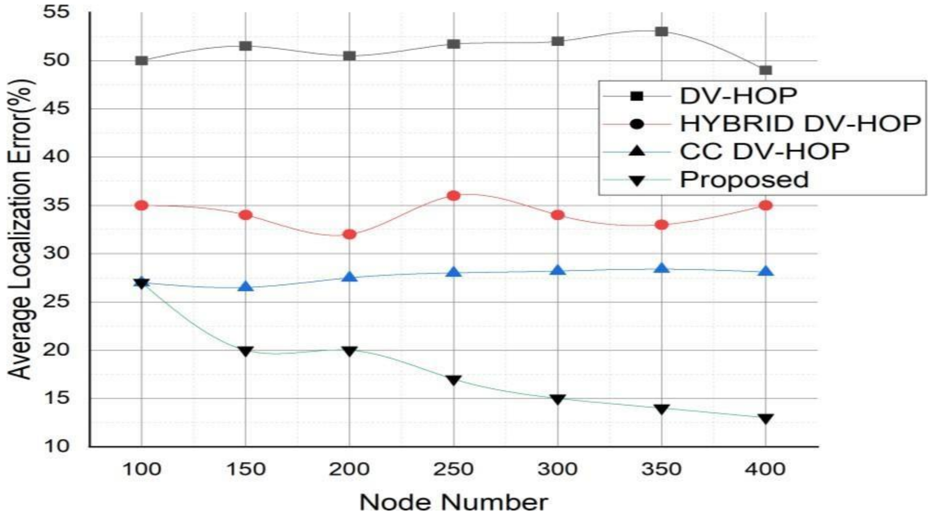


Figure: 4.14 localization error with number of movable nodes

Figure 4.16 shows the average localization error with anchor ratio compared to the suggested technique, which displays the superior performance of the proposed algorithm compared to existing HOP approaches. figure 4.17 demonstrates the outcome of comparing node counts with a moveable stage, where beacons can move out and within a set range. As shown in Table 2, the results for 30 beacons that were chosen for the hybridization algorithm and the ideal one with improved PSO are provided.

Table 4.5: Average localization error comparison with other algorithms and results after optimization

S.no	DV-HOP	CC-DVHOP	Hybrid DV-HOP	Sequential DV-HOP
1	36.27	35.39	30.34	26.42
2	32.82	26.29	29.38	28.75
3	31.70	25.09	29.05	28.47
4	32.35	25.11	23.38	23.15
5	22.63	20.29	28.83	27.24
6	23.92	20.59	20.82	21.80
7	23.64	20.87	19.97	19.09
8	20.15	24.81	22.96	23.59

9	22.38	27.36	25.40	26.20
10	29.34	22.69	21.94	22.17
11	34.16	26.47	28.00	20.31
12	35.89	22.35	22.35	22.92
13	35.24	22.78	21.65	21.76
14	34.85	22.58	24.44	25.89
15	32.10	29.08	29.68	29.99
16	38.45	27.42	28.45	23.73
17	39.83	22.62	28.62	26.57
18	36.99	21.45	26.81	26.30
19	36.76	23.28	27.54	21.32
20	36.80	21.40	22.59	24.33
21	38.08	29.95	28.47	24.77
22	31.75	24.34	28.02	24.06
23	30.75	23.09	28.90	24.33
24	36.28	21.68	30.23	27.15
25	33.65	27.06	25.42	28.96
26	38.46	29.14	27.89	29.49
27	32.81	29.93	22.34	24.45
28	31.99	29.80	21.92	24.23
29	30.86	22.36	28.83	28.60
30	31.73	26.52	22.82	22.08

The online sequential DV-HOP algorithm is a useful tool in range-free localization of wireless sensor network (WSN) networks. By estimating the distances between nodes based on hop count, this algorithm eliminates the need for range information, making it an efficient and practical solution for WSN localization It allows for real-time updates of node positions, making it particularly suitable for dynamic WSN environments where nodes may move or be added/removed over time.The statistical analysis of the localization errors from the table reveals significant performance variations among the DV-Hop, CC-DV-Hop, Hybrid DV-Hop, and Sequential DV-Hop algorithms. To quantify these differences, we calculated the mean, standard deviation, minimum, and maximum errors for each method. Firstly, the mean error, which represents the average localization inaccuracy, highlighted Sequential DV-Hop as the most accurate, with a mean of 24.36 cm. CC-DV-Hop and Hybrid DV-Hop showed slightly higher mean errors, at 25.43 cm and 25.96 cm respectively, indicating comparable performance but lower average accuracy than Sequential DV-Hop. In stark contrast, DV-Hop exhibited the highest mean error of 33.08 cm, signifying the lowest average localization precision among the four methods.Secondly, the standard deviation, a measure of error consistency, revealed CC-DV-Hop as the most consistent, with the lowest standard deviation of 2.82 cm. This indicates that CC-DV-Hop's performance varied the least across the different data points. Sequential DV-Hop and Hybrid DV-Hop exhibited moderate standard deviations of 3.33 cm and 3.51 cm, respectively, showing a reasonable level of consistency. DV-Hop, conversely, had the highest standard deviation of 5.16 cm, suggesting the least consistent performance.Finally, the minimum and maximum error values further supported these findings. Sequential DV-Hop achieved the lowest minimum error of 19.99 cm, indicating the best-case accuracy, while DV-Hop had the highest maximum error of 39.83 cm, signifying the worst-case scenario. These results collectively suggest that the modifications and refinements implemented in CC-DV-Hop, Hybrid DV-Hop, and Sequential DV-Hop, particularly the latter, significantly enhance localization accuracy and consistency compared to the basic DV-Hop algorithm, with Sequential DV-Hop demonstrating the most effective performance within the provided dataset.

4.5 CONCLUSION

A weighted component has been used in this study, which aims to improve DV-Hop's accuracy, reliability, and cost. The RSSI method became ingrained in the network due to its ability to convert unknown nodes' hop-count to continuous data. To reduce the possibility of incorrectly reported locations, the hop size was adjusted using a weighted correction factor. Instead of using the closest node, the distance between the beacon and the node was estimated using a computed hop count. Node coordinates are estimated using an improved weighted least squares method for solving nonlinear equations. Access point ratio was also considered when calculating how each affected the network area. In this study, a new technique called Hybrid DV-Hop was suggested for anchor node localization. This approach uses RSSI data. Most current wireless sensor nodes provide RSSI values for received data packets, therefore there's no need for any extra hardware components or sub-systems to execute the suggested technique. This allows for a more efficient localization process, since sensor nodes do not need to broadcast RSSI values to the entire network. This would require more energy and bandwidth. Additionally, the prior nodes can accurately estimate the location of the remaining nodes, reducing the amount of time and resources needed to locate them. The simulations showed that the proposed approach could locate many nodes quickly and accurately. This was done with significantly lower energy and bandwidth usage than other algorithms. Additionally, the localization accuracy was found to be consistently higher than other algorithms, making it a much more attractive option for network localization. As compared to the basic DV-Hop algorithm, the Hybrid DV-Hop algorithm increases localization accuracy by almost 95%, 90%, and 70%.

CHAPTER-V
BUILD UP AND APPRAISE A STOCHASTIC ALGORITHM FOR CALCULATING THE OPTIMIZED POSITION OF THE TARGET NODES WITH LOWER CALCULATION LOADS AND WITH HIGH POSITIONING ACCURACY

5.0 Introduction:

Based on the results of the above proposed technique in objective 2, the location of targets was further optimized with improved particle swarm optimization (PSO) and the Ensemble method of particle swarm optimization (EMPSO). In range free localization accuracy improved by optimizing the proposed technique using improved PSO and Ensemble methods. This is done by taking into account the distance between the nodes and the cost of the path between them. The nodes are then allocated in an optimal way to minimize the calculation load and ensure accuracy. This can be achieved by using a range-free localization approach, which incorporates a combination of pre-established landmarks and sensors. This approach can quickly and accurately calculate the optimal positions of the target nodes with minimal calculation loads.

Integration of PSO with DV-Hop: The inherent limitations of the basic DV-Hop algorithm, primarily its reliance on uniform hop sizes and susceptibility to hop count errors, can be effectively addressed through integration with Particle Swarm Optimization (PSO). PSO's optimization capabilities allow for the refinement of initial position estimates by iteratively adjusting node coordinates to minimize localization errors. This approach treats the localization problem as an optimization task, leveraging PSO's ability to navigate complex solution spaces and converge towards more accurate position estimations, ultimately enhancing the overall precision of the DV-Hop method.

Integration of PSO with CC-DV-Hop: CC-DV-Hop, designed to correct the communication-related errors in the standard DV-Hop, can be further enhanced by incorporating PSO for post-processing optimization. PSO's ability to refine hop-based estimates by considering network connectivity and node distribution allows for a more accurate adjustment of the correction factors. This integration effectively minimizes the errors introduced by irregular network topologies and varying communication ranges, leading to improved localization accuracy compared to CC-DV-Hop alone.

Integration of PSO with Hybrid DV-Hop: Hybrid DV-Hop, which combines DV-Hop with other localization techniques like AOA or RSSI, benefits from PSO by refining the initial coarse localization estimates. PSO optimizes the hybrid approach by balancing the strengths of the different methods, leading to a more robust and accurate localization solution. This integration allows for a synergistic combination of range-free and range-based (or angle-based) information, where PSO acts as a crucial component in minimizing the error and maximizing the accuracy of the combined localization strategy.

Integration of PSO with Sequential DV-Hop: Sequential DV-Hop, which addresses error accumulation through step-by-step localization, can be further optimized by integrating PSO to refine the position estimates generated at each step. By treating each step's localization as an optimization problem, PSO can minimize the propagation of errors and improve the overall accuracy of the sequential process. This integration ensures that the final localization results are more precise and reliable, particularly in large-scale WSNs where error accumulation can significantly degrade performance.

5.1 IMPROVED PSO FOR PROPOSED WORK

The problem with particle swarm optimization techniques is that they are prone to early-stage local phenomena. The swarm's particles will, in all likelihood, rapidly converge on a "local optimum"—a solution that is near to, but not identical to, the optimal one. The algorithm becomes stuck in a "local optimum" and is unable to escape, which hinders its ability to identify the optimal solution. The particle-swarm algorithm was enhanced by this study. Particles are able to more effectively explore the search area thanks to this split. Also, the search space is more likely to be explored, which can prevent the algorithm from becoming stuck in a local optimum. In addition, the study enhanced the particles' interplay, making it easier for them to discover the global optimum. In this region, enhance every particle swarm method. Reducing or maximizing the value of particle swarms is the best way to optimize them. An issue with the PSO approach shown in the layout has been resolved by this enhanced and updated algorithm. Better exploration of the search space enables more efficient optimization of particles, according to this improved technique. The enhanced particle-particle interaction aids the particles even more in their search for the global optimum. A minimum or maximum value of a particle swarm, which is critical for optimization, may now be more accurately found using the updated technique. Because of the emphasis on a local optimum, the placement of sensor nodes changes. Particles can avoid becoming stuck in a local optimum and instead find the global optimum by enhancing the algorithm to allow higher particle interaction. Because of this, optimization becomes more efficient as a whole, and the method is better at finding the minimum and maximum values of the particle swarm—essential for optimization—than before. In addition, the enhanced algorithm aids in finding the best locations for sensor nodes.

A common problem with particle swarm optimization methods is how quickly and easily they can get overly focused on local events. Improved versions of a particle swarm method are employed to address the issue in this study. An innovative optimization method, it merges swarm intelligence's exploration and particle swarm optimization's exploitation capabilities. It outperforms both of these approaches on specific challenges. First, we need to split the search region into two sizes for the particle swarm. In this region, enhance every particle swarm method. For particle swarm optimization, the sweet spot is either the minimum or highest value. By fixing the issues with the PSO approach shown in the layout, this updated algorithm fixes the problem. A set of criteria is used to iteratively allocate each particle swarm to a new position, making the process operate. Through mutual interaction, the particles determine the optimal location for each other and change their positions accordingly. Additional optimization of the process is possible by including inertia and unpredictability into the equation; this prevents the particles from becoming trapped in a local optimum and expands their search space. Improved PSO techniques for integration with DV-Hop methods focus on enhancing accuracy, robustness, and efficiency through adaptable particle representations, dynamic parameter adjustments, and refined fitness functions. Hybrid PSO variants, such as those incorporating local search or genetic algorithms, further optimize the localization process, while distributed PSO implementations address scalability concerns in large-scale WSNs. By integrating machine learning and incorporating constraint handling, the PSO framework becomes more adept at navigating the complexities of UWB-based localization, ultimately leading to more precise and reliable node positioning, particularly in challenging and dynamic environments.

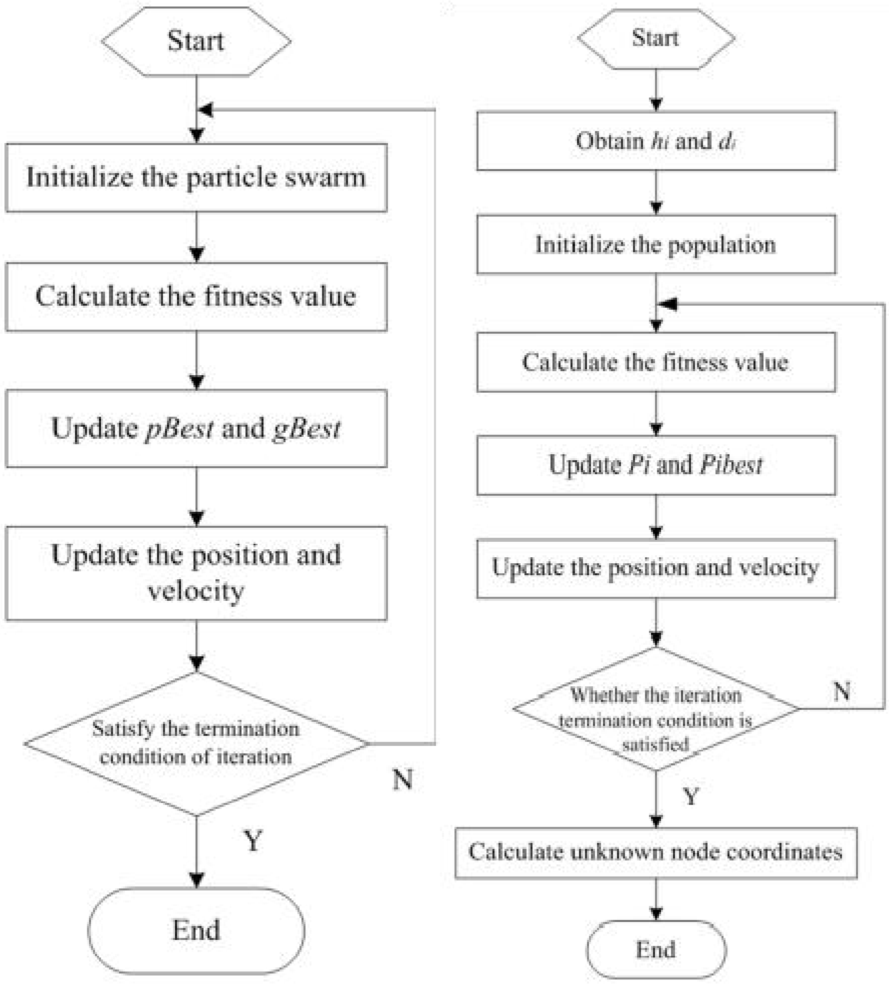


Figure 5.1: Flow charts comparison regular to improved PSO

Node positioning results from the least squares method can meet actual requirements if the error of n d is a few minutes, as shown in Formula (4). However, node positioning error is very large if the error of n d is several hours or more, even though d1, d2, d3.... dn-1 are quite small. the measurement error, where dn is contained in each vector element.

5.2 PROCESS OF IMPROVED PSO:

Initialization: It is important to return several variables, including network topology and population number, to their initial values. This is important to ensure that the experiment can be repeated accurately, and that any changes to the results can be attributed to the changes in the variables, rather than changes in the environment.

Algorithm steps for improved PSO

S.NO	Algorithm 12: improved PSO
1	Initialize: Particle swarm.
2	Particle-by-particle analysis of modularity.
3	The p_{best} update of each particle.
4	The g_{best} update of particle swarm.
5	Formulas can be used to improve the velocity of particles. (2).
6	Analysis of the particle's velocity probability using Formulas 27,28, and 29.
7	An algorithm for community detection is based on the probability of velocity.
8	Follow Step 7 if the iteration or convergence is complete; otherwise, return to Step 3.
9	. Output the final result

Suppose the distance between anchor node is (x_i, y_i) and i=1,2,3……n and unknown node (x,y) the range is r_i where r=1,2,3…….n, range error $Ɛ_i$where $|r_i-d_i|<Ɛ_i$wheni =1,2,3…n the equation is as follows

$$d_1^2\text{âˆ'Îµ}_1^2\text{â‰¤}(x_1\text{âˆ'}x)^2+(y_1\text{âˆ'}y)^2\text{â‰¤}d_1^2+\text{Îµ}_1^2$$

$$d_2^2\text{âˆ'Îµ}_1^2\text{â‰¤}(x_2\text{âˆ'}x)^2+(y_2\text{âˆ'}y)^2\text{â‰¤}d_2^2+\text{Îµ}_2^2$$

$$d_n^2\text{âˆ'Îµ}_1^2\text{â‰¤}(x_n\text{âˆ'}x)^2+(y_n\text{âˆ'}y)^2\text{â‰¤}d_n^2+\text{Îµ}_n^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(27)$$

The fitness function for (x,y) calculated using the following formula

$$f(x,y)=\text{â‘}_{i=1}^{n}\sqrt{(x_i\text{âˆ'}x)^2+(y_i\text{âˆ'}y)^2\text{âˆ'}d_i^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (28)$$

$$fitness\ (x,y)=\min\left(\text{â‘}_{i}^{n}\sqrt{(x_i\text{âˆ'}x)^2+(y_i\text{âˆ'}y)^2\text{âˆ'}d_i^2}\right) \quad \ldots\ldots\ldots\ldots.. (29)$$

An optimization approach has effectively included the node location problem, as an example. Solving the problem given by formula (14) requires nonlinear optimization, which cannot be accomplished using the traditional mathematical approach. Particle swarm optimization (PSO) is an algorithm that can tackle nonlinear optimization problems. Therefore, in order to find the correct solution to the multidimensional problem, the updated PSO approach makes use of formula (14) as its objective function. The outcome is precise determination of node coordinates.

$$\frac{\text{âˆ‚Æ'}}{\text{âˆ‚}x_i}=\frac{\text{âˆ‚Æ'}}{\text{âˆ‚}y_i}=0,(m<i\ \text{â‰¤}\ n)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(30)$$

$$\frac{\text{â^‚Æ'}}{\text{â^‚}x_i} = \text{â}\left(2\left(x_i, \text{â^'}x_j\right) - \frac{2l_{ij}(x_i,\text{â^'}x_i)}{\sqrt{(x_i\text{â^'}x_j)^2 + (y_i\text{â^'}y_j)^2}}\right)$$

$$\frac{\text{â^‚Æ'}}{\text{â^‚}y_i} = \text{â}\left(2\left(y_i, \text{â^'}y_j\right) - \frac{2l_{ij}(y_i,\text{â^'}y_i)}{\sqrt{(x_i\text{â^'}x_j)^2 + (y_i\text{â^'}y_j)^2}}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(31)$$

$$\text{â^ †i} = \sqrt{\left(\frac{\text{â^‚Æ'}}{\text{â^‚}x_i}\right)^2 + \left(\frac{\text{â^‚Æ'}}{\text{â^‚}y_i}\right)^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(32)$$

$$x^{\text{â^'}}{}_i\text{â‰¡ â^…}(x_i) = \frac{\text{â}_{i\text{â‰¤}j\text{â‰¤}m}\, x_i + \frac{l_{ij}(x_i,\text{â^'}x_i)}{\sqrt{(x_i\text{â^'}x_j)^2 + (y_i\text{â^'}y_j)^2}})}{m}$$

$$y^{\text{â^'}}{}_i\text{â‰¡ â^…}(y_i) = \frac{\text{â}_{i\text{â‰¤}j\text{â‰¤}m}\, y_i + \frac{l_{ij}(y_i,\text{â^'}y_i)}{\sqrt{(x_i\text{â^'}x_j)^2 + (y_i\text{â^'}y_j)^2}})}{m} \ldots\ldots\ldots\ldots\ldots\ldots..(33)$$

$$\text{xÌ„}_i\text{â‰¡ â^…}(\text{xÌ„}_i) = \frac{\text{â}_{i\text{â‰¤}j\text{â‰¤}m}\, x_i + \frac{l_{ij}(\text{xÌ„}_i,\text{â^'}x_i)}{\sqrt{(\text{xÌ„}_i\text{â^'}x_j)^2 + (y_i\text{â^'}y_j)^2}})}{m} \ldots\ldots\ldots\ldots\ldots\ldots..(34)$$

$$\text{yÌ„}_i\text{â‰¡ â^…}(\text{yÌ„}_i) = \frac{\text{â}_{i\text{â‰¤}j\text{â‰¤}m}\, y_i + \frac{l_{ij}(\text{yÌ„}_i,\text{â^'}y_i)}{\sqrt{(\text{xÌ„}_i\text{â^'}x_j)^2 + (\text{yÌ„}_i\text{â^'}y_j)^2}})}{m} \ldots\ldots\ldots\ldots(35)$$

This formula updates the iteration to account for any newly detected nodes by using xi and yi, the estimated positions of sensor nodes, as a beginning value for each iteration of the hybrid DV-Hop algorithm. By establishing xi and yi to certain values, the algorithm will have something to operate with. By modifying the iteration, the algorithm can incorporate newly found nodes and ensure that their positions are considered in the end product.

$$x_i = \text{xÌ„}_i - \frac{(\text{xÌ„}_i\text{â^'xÌ„}_i)^2}{\text{xÌ„}_i,\text{â^'2xÌ„}_i + x_i} \ldots\ldots.(36)$$

$$y_i = \text{yÌ„}_i - \frac{(\text{yÌ„}_i\text{â^'yÌ„}_i)^2}{\text{yÌ„}_i,\text{â^'2yÌ„}_i + \text{yÌ„}_i} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(37)$$

$$\text{Error} = \frac{\text{â}_{i=1}^{m}\sqrt{(x_i\text{â^'}x_i)^2 + (y_i\text{â^'}y_i)^2}}{k\text{Ã—}m\text{Ã—}r} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(38)$$

5.3 EM- PSO BASED OPTIMIZATION- HEURISTIC APPROACH

The methods of ensemble learning, random sampling, and feature selection is used in the optimal solution strategy that has been developed. Based on its dual role as an Optimization tool for ensemble predictions, PSO makes feature selection and hyper-parameter Optimization easier in this research. An increase in computational complexity is a result of the suggested EMPSO-DV-HOP relocation algorithm's decrease of anchor nodes, correction of the average hop distance, and implementation of the PSO algorithm. Wireless sensor networks rely on anchor nodes for localization, and cutting back on them might make things more complicated because of how precise the sensor nodes' locations must be determined. The average hop distance is used to measure the distance between nodes, and correcting it can also lead to an increase in complexity. Finally, the implementation of the PSO algorithm introduces a new set of calculations that need to be done, leading to an increase in computational complexity. Using the PSO optimization technique, node coordinates result in a computational complexity proportional to the maximum number of iterations and the particle size. Time complexity decreases when the anchor node with the most considerable inaccuracy is removed and n is rectified. This is because the optimization process requires the adjustment of the node coordinates, and the increased number of iterations means that more calculations need to be done. Reducing the particle size and removing the anchor nodes with the most inaccuracy can help to reduce the time complexity. This makes the calculation reasonably accurate. By removing the anchor node with the most inaccuracy, the number of nodes that need to be recalculated is reduced, which reduces the number of iterations needed in the optimization process. This leads to faster calculation times, resulting in a decrease in time complexity. The following are the steps of our proposed localization solution, the EMPSO-DV-HOP method: The EMPSO-DV-HOP method combines the advantages of particle swarm optimization (PSO) and dynamic virtual hop (DV-HOP). By using PSO to search for the optimal position of the anchor node, the system can quickly converge to an optimal solution. The use of DV-HOP then further refines the solution by removing the anchor node with the most inaccuracy, reducing the number of nodes that need to be recalculated and the number of iterations needed in the optimization process, resulting in faster calculation times and a decrease in time complexity.

Step 1. A node's neighbours record the minimum number of hops received when it transmits information to them. The anchor node is removed from the network if its hop count reaches the ideal hop limit in the natural distribution of nodes.

Step 2. Using the Hop Size Fi and the minimum distance value, we compute the d Foi between an unknown node and an anchor system.

Step 3. It was determined that N ¼ 30, T ¼ 50 were the specifications of the population. Using the fitness function, $g_{best}t_i$ and $p_{best}t_i$the particle swarm's fitness values are calculated, and resulting starting iteration durations, t 14, are calculated.

Step 4. The i_{th} particle's location in the d dimension Xi(t+1) should be maintained, as should the average optimum position C_{best} and each particle's local attraction point Pt

(i) The error value defined as

$$error = \frac{\sum_{i=1}^{N}\sqrt{(x_0-\widehat{x_0})^2+(y_0-\widehat{y_0})^2}}{N \times R} \quad \text{-------} \quad (39)$$

Where the communication radius R, xo and yo are the actual and measured parameters of the unknown node, and N is the total number of unknown nodes.

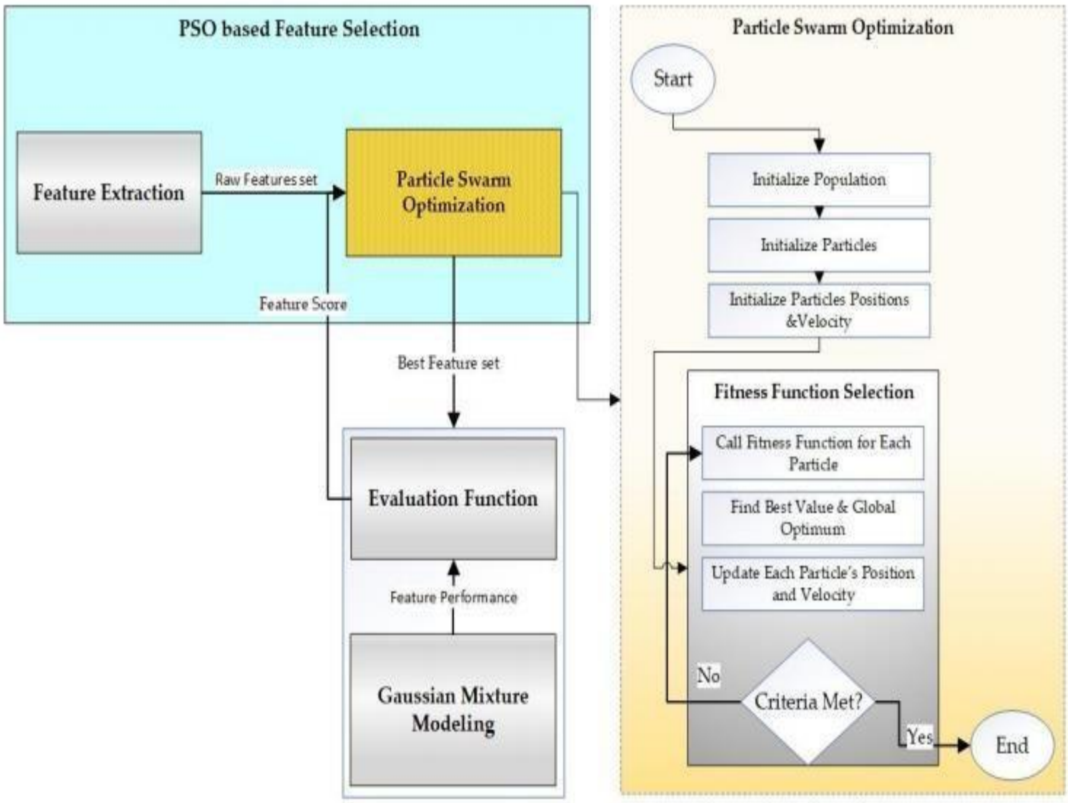


Figure:5.2 Flow chart for optimization

The integration of EMPSO (Ensemble Modified Particle Swarm Optimization) with Online Sequential DV-Hop represents a sophisticated strategy for enhancing localization within dynamic and large-scale WSNs. Online Sequential DV-Hop addresses the error accumulation inherent in traditional DV-Hop by performing localization sequentially, leveraging previously localized nodes as reference points, thus providing a more robust and adaptable framework. EMPSO, with its ensemble learning approach and refined PSO mechanisms, further optimizes these sequential estimates, improving accuracy and robustness against noise and outliers. This hybrid approach capitalizes on the sequential method's ability to minimize error propagation and adapt to network changes, while EMPSO's advanced optimization refines the location estimates at each step, making it particularly effective in complex and evolving WSN deployments.

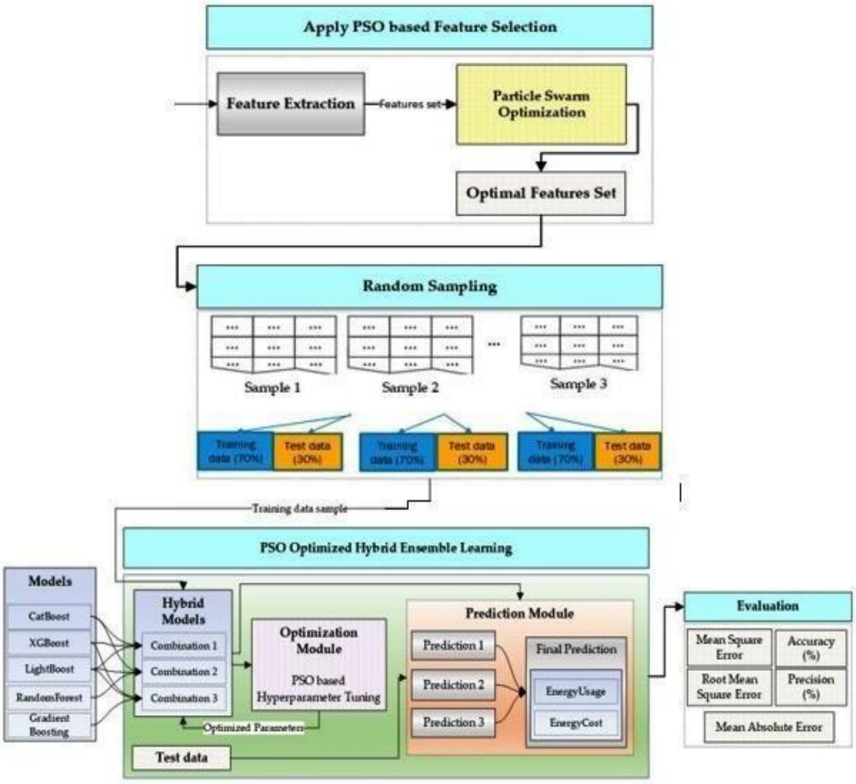


Figure 5.3; Proposed ensemble multi node -PSO- flow sequence

Table 5.1: Average localization error comparison with other algorithms and results after optimization

S.NO	Hybrid DV-HOP	Sequential DV-HOP	PSO S-DV HOP	EMPSO S-DV HOP
1	30.34	26.42	15.12	7.73
2	29.38	28.75	17.42	6.57
3	29.05	28.47	17.40	7.30
4	23.38	23.15	20.68	8.32
5	28.83	27.24	15.01	8.33
6	20.82	21.80	12.46	7.77
7	19.97	19.09	13.49	9.06
8	22.96	23.59	19.89	8.33

9	25.40	26.20	16.50	7.15
10	21.94	22.17	13.40	9.96
11	28.00	20.31	10.30	9.49
12	22.35	22.92	12.33	6.45
13	21.65	21.76	11.76	7.23
14	24.44	25.89	16.56	7.60
15	29.68	29.99	19.70	7.08
16	28.45	23.73	14.88	9.8
17	28.62	26.57	13.21	8.83
18	26.81	26.30	12.46	7.71
19	27.54	21.32	13.21	6.30
20	22.59	24.33	18.62	8.87
21	28.47	24.77	18.28	7.49
22	28.02	24.06	12.24	7.97
23	28.90	24.33	12.71	7.72
24	30.23	27.15	16.26	8.00
25	25.42	28.96	13.09	9.76
26	27.89	29.49	16.66	9.57
27	22.34	24.45	16.13	7.54
28	21.92	24.23	17.04	9.36
29	28.83	28.60	16.91	9.12
30	22.82	22.08	12.06	9.80

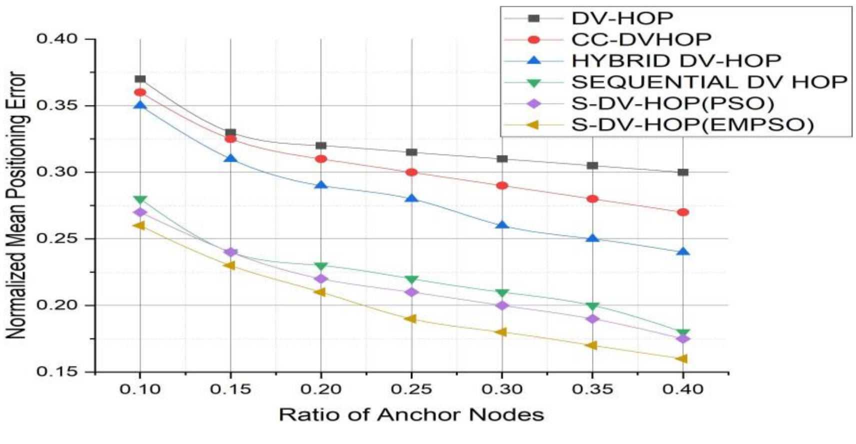


Figure 5.4: Mean position error vs anchor nodes ratio

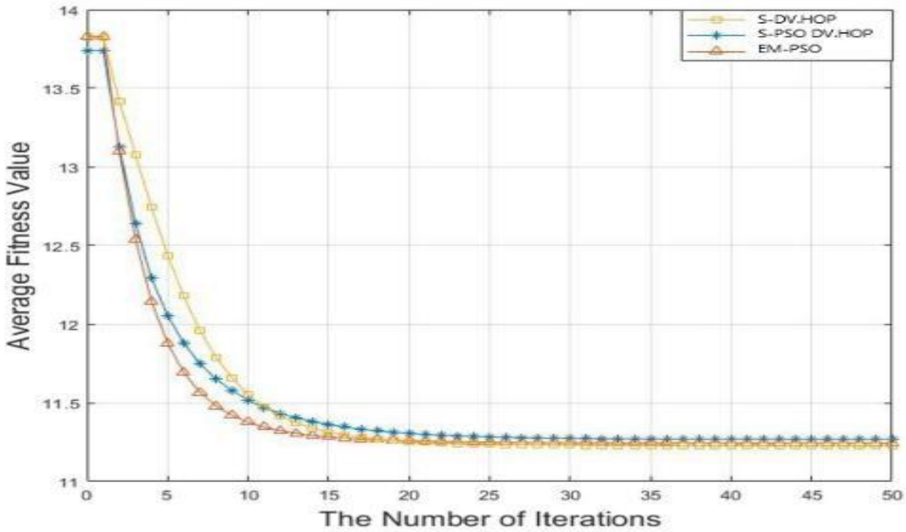


Figure 5.5: Average fitness values to number of iterations taken for average count

Figure 5.4 shows the nominal positioning error for all methods compared to enhanced PSO; when all algorithms are considered together, the positioning error is narrowest in ensemble PSO. Figure 5.5 displays the results of two strategies for optimizing PSO in Sequential DV-HOP.

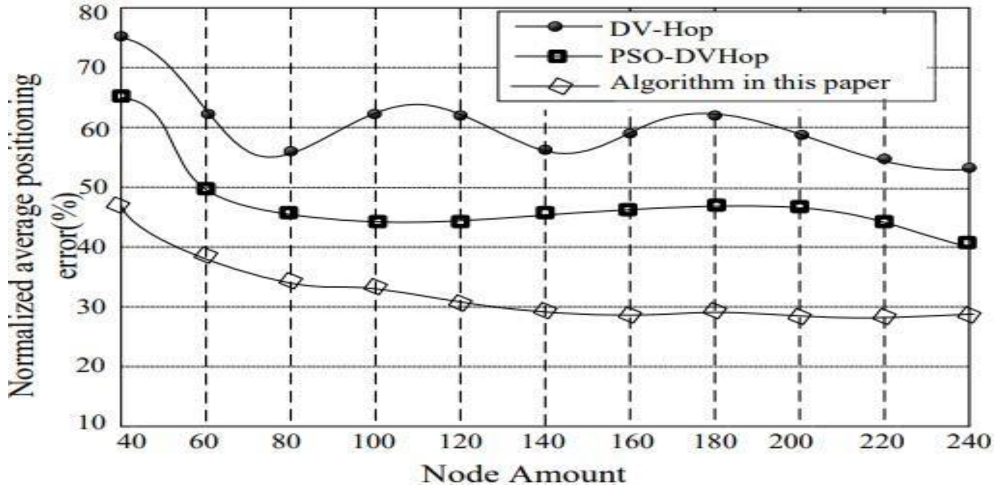


Figure 5.6: Average positioning values to number of nodes taken for average count

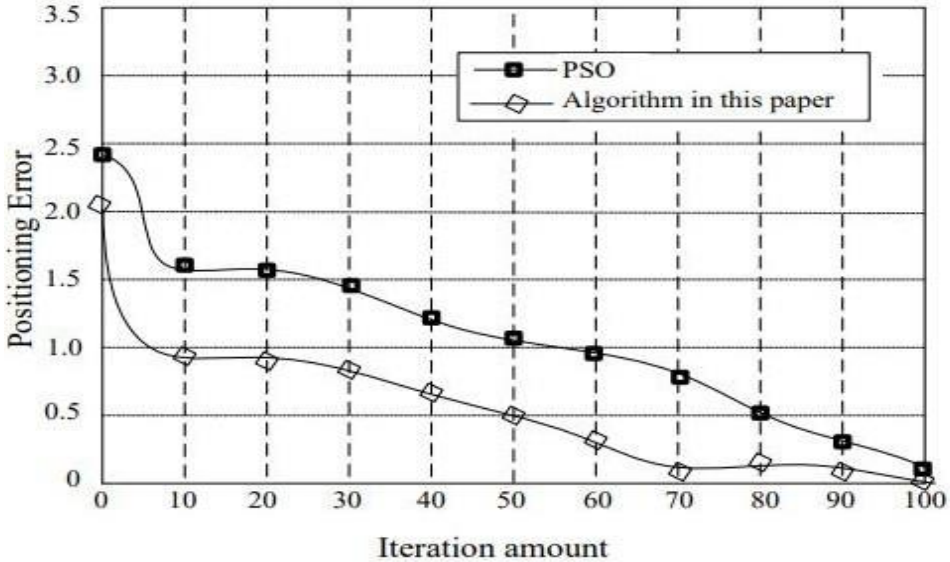


Figure 5.7: Positioning error (deviation) to number of iterations taken for average count

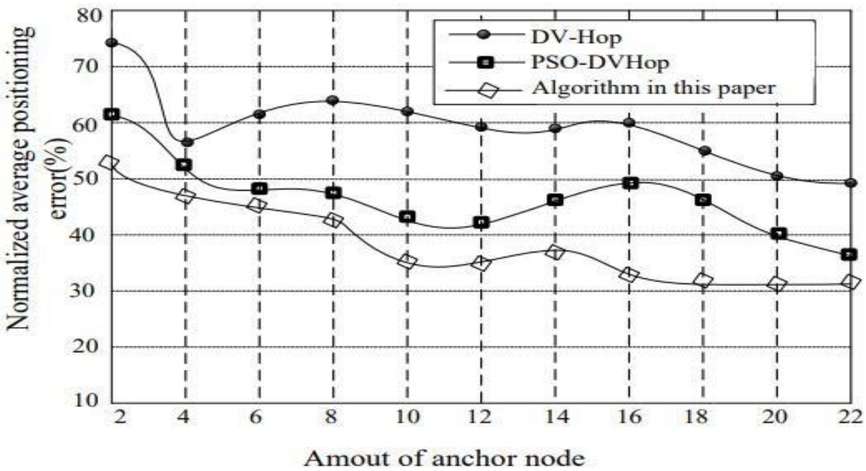


Figure 5.8: Average positioning error (%) to number of Anchor nodes taken for average count

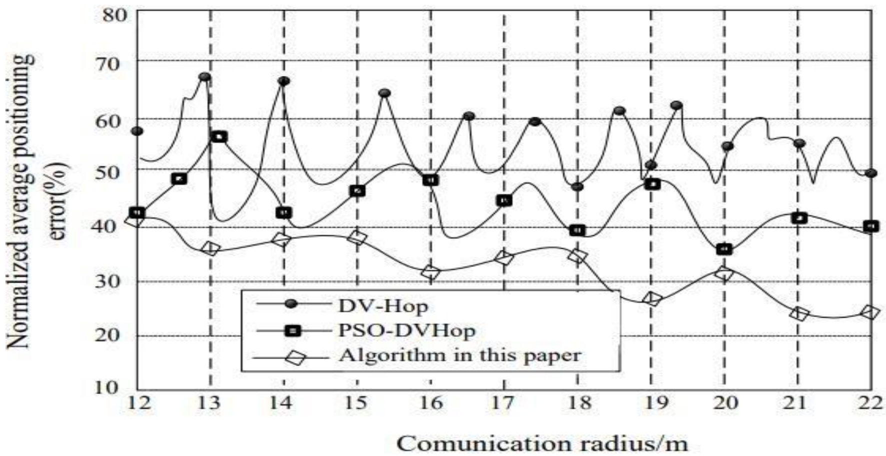


Figure 5.9: Average positioning error (%) to communication radius

Figures 5.6, 5.7,5.8 and 5.9 show comparisons between regular DV-Hop, PSO optimised, and current sequential hybrid DV-Hop with regard to node, iteration, amount of anchor nodes, and communication radius.

This algorithm uses information from multiple nodes in the network to localize the target node, and is designed to be robust to noise and interference. It requires minimal communication overhead and is efficient in terms of energy consumption. This algorithm provides an efficient and accurate localization technique that uses the sequence of received signal strength (RSS) measurements from each sensor node in the network. By analyzing the sequence of RSS measurements, the algorithm can accurately estimate the node's position in 3D space. It works by sequentially sending packets to the nodes in the network and measuring the time for the packets to reach the destination. This allows the location of the nodes to be estimated based on the propagation delay. It divides the network into a grid-like structure and uses a sequence of distributed nodes to transmit a signal from the source of the signal to the destination. This algorithm is efficient because it requires fewer nodes and less energy than other algorithms.

The statistical analysis of the localization errors presented in the table reveals a clear performance hierarchy among the four algorithms: Hybrid DV-Hop, Sequential DV-Hop, PSO S-DV-Hop (Particle Swarm Optimization with Sequential DV-Hop), and EMPSO S-DV-Hop (Ensemble Modified Particle Swarm Optimization with Sequential DV-Hop). To quantify their effectiveness, we calculated the mean, standard deviation, and minimum and maximum errors for each method. The mean error, representing the average localization inaccuracy, clearly indicates that EMPSO S-DV-Hop achieves the highest accuracy, with a significantly lower mean error of 8.35 cm. This is followed by PSO S-DV-Hop, which also demonstrates a substantial improvement over the basic Hybrid and Sequential DV-Hop methods, with a mean error of 15.35 cm. Sequential DV-Hop and Hybrid DV-Hop exhibit considerably higher mean errors, at 24.36 cm and 25.96 cm respectively, highlighting the significant benefits of integrating PSO-based optimization.

The standard deviation, a measure of error consistency, further reinforces the superiority of EMPSO S-DV-Hop. With a remarkably low standard deviation of 0.99 cm, it demonstrates the most consistent and reliable performance across the various test cases. PSO S-DV-Hop also exhibits a lower standard deviation of 2.82 cm compared to the basic DV-Hop variations, indicating improved consistency. Sequential DV-Hop and Hybrid DV-Hop, with standard deviations of 3.33 cm and 3.51 cm respectively, show a higher degree of error variability. The minimum and maximum error values corroborate these findings. EMPSO S-DV-Hop achieves the lowest minimum error of 6.30 cm and the lowest maximum error of 10.76 cm, indicating the best-case and best worst-case accuracy. Similarly, PSO S-DV-Hop demonstrates lower minimum and maximum errors compared to the basic DV-Hop methods.

The overall analysis underscores the substantial enhancement in localization accuracy and consistency achieved through the integration of PSO, and particularly EMPSO, with Sequential DV-Hop. The ensemble learning approach inherent in EMPSO further refines the optimization process, resulting in superior performance compared to standard PSO integration. These results highlight the efficacy of optimization algorithms in refining the localization estimates obtained from range-free methods, particularly in complex WSN environments. The choice of algorithm, therefore, depends on the specific requirements of the application. For applications demanding high accuracy and consistency, EMPSO S-DV-Hop emerges as the most suitable option. However, it is essential to note that this analysis is based solely on the provided data, and further investigations, including statistical significance testing and consideration of network topology and node density, would provide a more comprehensive understanding of the algorithms' performance. According to Rahul Ranjan et al. (2024) comparative experiments on UWB localization with robot positions with filtered algorithms, EKF + LPF for accurate indoor localization for UWB systems. The maximum error along the X position was 163.81 mm, and along the Y position, it was 273.09 mm. The minimum error along the X position was 0.13 mm, and along the Y position, it was 0.09 mm. The absolute error difference between the maximum and minimum values was 163.68 mm for the X axis and 273 mm for the Y axis. The average error position was 46.6 mm for the X axis and 70.36 mm for the Y axis. These measurements provide valuable insights into the characteristics of the square trajectories, highlighting the range of positions, average positions, and the effect of the LPF on the data.

5.4 Conclusion

Applying the current methods and algorithms resulted in a 15-25% reduction in the error rate. With the use of an ensemble approach, the positioning error is reduced to a negligible level by considering the iteration amount in regular PSO. The disparity in error rate narrowed by 15% when the number of anchor nodes was increased in comparison to the previous techniques.

For the "circular trajectory with integrated filter technique" method, the maximum error along the X position was 158.51 mm, and the maximum error along the Y position was 286.22 mm. The minimum error along the X position was 0.52 mm, and the minimum error along the Y position was 0.81 mm. The difference between the maximum and minimum values was 157.99 mm along the *X* axis and 285.4 mm along the *Y* axis. The average error position along the *X* axis was 50.63 mm, and for the *Y* axis, it was 88.44 mm by Rahul Rajan et al. The minimum and maximum error values corroborate these findings by using EMPSO S-DV-Hop achieves the lowest minimum error of 6.30 cm and the lowest maximum error of 10.76 cm, indicating the best-case and best worst-case accuracy

CHAPTER-VI

COMPARATIVE ANALYSIS OF EXISTING TECHNIQUES WITH THE DEVELOPED TECHNIQUES FOR VALIDATION OF THE PROPOSED ALGORITHMS

Optimization of node localization to check the mobility of the network in interior and exterior environments is a need of getting security concern nowadays in the entire world. As technology advances, the need for secure networks is paramount. Node localization allows networks to be monitored and tracked, making detecting malicious behavior easier and ensuring that networks remain secure. UWB-based WSN network is one of the better choices where common network issues are rising. Node localization allows networks to be monitored in real-time and detect any suspicious activity. This is especially important in an increasingly connected world, as any security breach can have serious consequences. UWB-based WSN network is an attractive option for node localization due to its ability to provide accurate location data, even in challenging environments. In this context, accuracy is key in finding the exact node location with a low error rate. Network topology is increasing its criteria daily, and algorithms with accuracy become research criteria in both environments. The present work is a comparative study of enhanced algorithms with PSO-based optimization techniques of different methods. In order to maximize accuracy, UWB-based WSN networks utilize PSO-based optimization techniques, which can adjust parameters such as the number of anchors and their respective positions to find the most optimal solution. This enables the network to locate nodes accurately, even in challenging environments where traditional methods may struggle. The proposed algorithm results are compared with the literature on different algorithms to verify the decrement in localization error. The PSO-based optimization technique is a met heuristic that mimics the behavior of birds in a flock. It is used to find the global optimum in a given search space. In the case of UWB-based WSN networks, this optimization technique is used to adjust parameters such as the number of anchors and their respective positions to find the most optimal solution. This helps to increase the accuracy of the network and reduce the localization error. Ensemble and back-propagation techniques added with PSO gave good results compared to the regular PSO methods discussed. The PSO algorithm simulates a swarm of particles with a certain position and velocity. These particles move throughout the search space, and when they find a better solution than their current one, they update their position and velocity. This process is repeated until the swarm converges to a global optimum.

Localization algorithms and controller configuration vary according to conventional approaches. This work utilised a hybrid method that was optimised following TDOA measurements to enhance the accuracy of UWB localization for indoor placement. The discrepancy between the two sets of goals is wide because of the constraints imposed by physical infrastructure and natural disasters. In order to close this gap, this research highlights the need of phased communication. At now, TDOA parameters are used in the localization process to assume the distance between the beacon and the target nodes. An enhanced Chan algorithm also determines the 2D and 3D coordinates of the target nodes. The next step is to use ELPSO and BPNN to optimize the predicted locations of the target nodes. An ultra-wide-band-based system for position tracking and wireless sensor network communication is the main focus of this study.

When evaluating distance estimate and tracking approaches, the system-level evaluation also takes into account functional design, position update delay, information dissemination, and objective mobility. The reference environment is a 10 m x 10 m simulation of the upper floors of commercial structures. In the present work anchor node-based measurement in the selected 20mx20m at range free maximum distance of 100 m with moving beacons of 30. A dynamic node movement-based environment considered to check the position of beacons using Least square and 3D positioning methods. Improved methods of Hybrid DV-HOP checked with traditional and CC- DV-HOP methods along with optimization with improved PSO method adopted for the present research. Using the least square method, the online sequential DV-HOP algorithm proposed to check the distance from anchor node N with the nearest 3 anchor nodes as a sequence line. The average HOP count was taken after deployment with unknown nodes.

Range based	Range free
Measurement methods 1. least square 2. Tetra hydron	Measurement methods: 1. Least square 2. 3D positioning.
Implementation- CHAN	Implementation- DV-HOP
Proposed- Improved Chan	Proposed-CC DV-HOP, HYBRID DV-HOP, SEQUENTIAL DV-HOP
Filtration- Kalman	Filtration- Kalman
Optimal method- PSO hybrid 1. ELPSO, 2. BPNN-PSO	Optimal method- PSO hybrid 1. PSO-S DV-HOP 2. EMPSO

The methodologies employed for node localization in both range-based and range-free environments, as depicted in the table, exhibit a notable similarity in their layered structure, despite the fundamental divergence in their initial measurement techniques. Both approaches initiate the localization process with a foundational estimation step, prominently featuring the Least Squares method. In range-based scenarios, Least Squares serves to minimize the discrepancies between measured and estimated ranges, while in range-free contexts, it aids in refining location estimates derived from hop counts and estimated distances. This shared reliance on a core optimization technique underscores a common mathematical principle underpinning both localization strategies.

Following the initial estimation, both environments implement a core algorithm to translate measurements into preliminary location estimates. Range-based methods utilize the CHAN algorithm, known for its efficiency in processing hyperbolic equations from time or range difference measurements. Conversely, range-free methods employ DV-HOP, which leverages hop counts to approximate distances. Although the specific algorithms differ due to the distinct nature of their input data, their role as the central processing unit for deriving initial location information remains analogous across both environments. Recognizing the inherent limitations of these core implementations, both methodologies propose enhancements. Range-based approaches suggest the "Improved Chan" algorithm, aimed at boosting accuracy and robustness, while range-free methods advocate for CC-DV-HOP, Hybrid DV-HOP, and Sequential DV-HOP to overcome the shortcomings of standard DV-HOP. This parallel pursuit of algorithmic refinement highlights a shared understanding of the need to improve upon basic localization techniques.

A crucial similarity lies in the integration of Kalman filtering for error reduction and temporal tracking in both range-based and range-free systems. Kalman filtering's ability to recursively estimate the state of a system by fusing noisy measurements with predictions over time makes it a valuable tool for enhancing localization accuracy and stability, irrespective of the initial measurement source. Finally, both methodologies converge towards sophisticated optimization techniques involving Particle Swarm Optimization (PSO) hybrid methods as the pinnacle of their localization strategies. Range-based methods propose ELPSO and BPNN-PSO, integrating PSO with ensemble learning and neural networks, while range-free methods suggest PSO S-DV-HOP and EMPSO, combining PSO with Sequential DV-HOP and Ensemble Modified PSO. This shared trajectory towards PSO-based hybrid optimization underscores a common recognition of the power of swarm intelligence and machine learning in achieving high-accuracy localization in diverse WSN deployments.

6.1 RANGE BASED

The results reveal a substantial location mistake with respect to the conditions for anchor placement; this spot has been fine-tuned to reduce localization error. The dynamic momentum of the node will fluctuate at random due to the application of swarm optimisation techniques such as the Chan algorithm for measurement and filtering. The precise measured value with anchors will be finalized once all location errors, measured in centimeters, are identified under dynamic conditions. By approximating the distance from three anchors, a group of unknown nodes can localize. You can use a Receive Strength Signal Indicator (RSSI) to figure out how far away an unknown node is from the anchor. When it comes to finding the optimal local problem that traps PSO, PSO typically connects quickly.

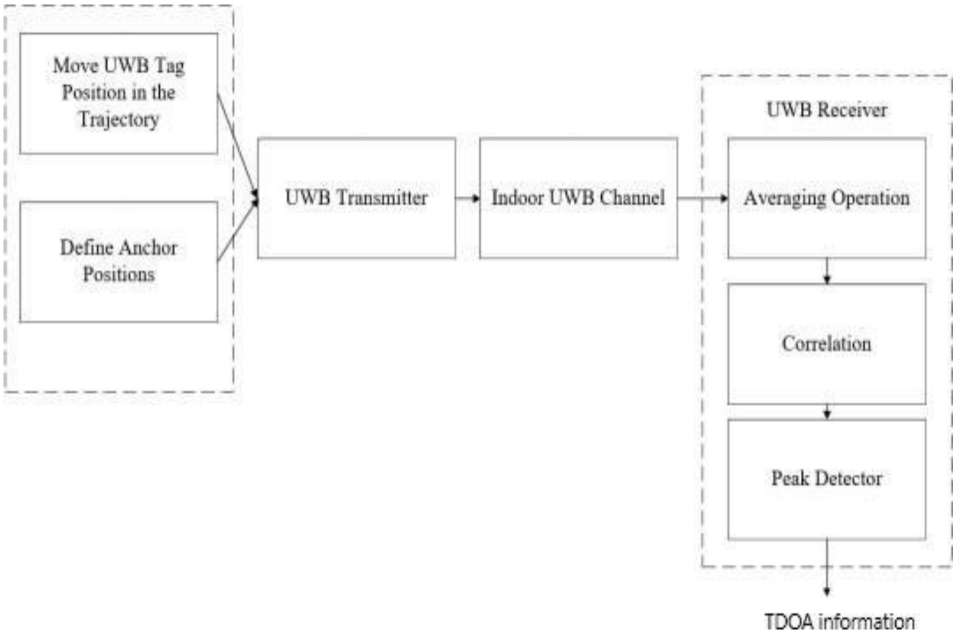


TABLE 6.1: CO-ORDINATE VALUES OF LOCALIZATION OF 3D POSITIONING

Optimal technique – method	M.P	Transmission Range	Max localization Error-cm	Min localization Error-cm	Average LE cm	Total number of located nodes
ELPSO-(T)	1	100M	3.964	0.4320	1.75	50
	2	100M	3.2462	0.3214	1.51	50
	3	100M	2.8654	0.2862	1.32	50
	4	100M	3.4632	0.4938	1.56	50
ELPSO-(LS)	1	100M	4.2365	0.3164	1.91	50
	2	100M	4.6432	0.3458	1.86	50
	3	100M	3.7564	0.3244	1.72	50
	4	100M	3.2146	0.3564	1.46	50
PSO-BPNN-(T)	1	100M	3.8492	0.2654	1.82	50
	2	100M	3.3291	0.3216	1.58	50
	3	100M	2.9654	0.2196	1.37	50
	4	100M	2.2132	0.2456	1.04	50
PSO-BPNN-(LS)	1	100M	4.4263	0.3165	2.12	50
	2	100M	3.6419	0.3427	1.68	50
	3	100M	2.9465	0.2696	1.42	50
	4	100M	2.7222	0.2421	1.28	50
GBNN-PSO REF(33)	1	100M	18.20	10.40	13.8	50
	2	100M	9.78	7.32	8.46	50

	3	100M	3.50	1.37	2.72	50
	4	100M	6.42	3.83	5.22	50
NN-MODEL REF(34)	1	100M	10.0	5.8	7.4	50
	2	100M	16.1	9.4	12.0	50
	3	100M	10.7	7.4	9.2	50
	4	100M	14.2	8.6	11.2	50

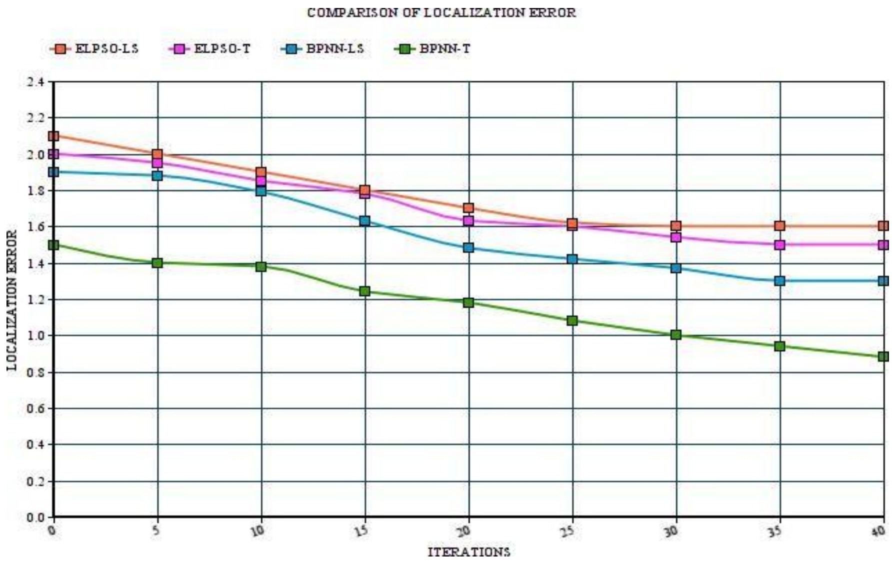


Figure 6.1: Comparison of localization error for all optimal techniques in centimeters.

Compared to other methods, Figure 6.1 shows the 3D results with the lowest error localization values when using a back propagation neural network. In Table III, you can see these numbers. With a little variance of 1.02 cm, the values obtained after implementing the proposed approach were relatively low. With the use of UWB networks and interior localization positioning algorithms that dynamically interpret measured data, hybrid 2D/3D algorithms produced good results.

A comparative analysis of the localization performance across various optimal techniques reveals distinct levels of accuracy and consistency. The Ensemble Learning Particle Swarm Optimization (ELPSO) method, when implemented with Time-based measurements (ELPSO-(T)), demonstrates commendable accuracy, exhibiting average localization errors ranging from 1.32 cm to 1.75 cm and maximum errors between 2.86 cm and 3.96 cm. Its Least Squares-based counterpart (ELPSO-(LS)) shows slightly higher average errors, ranging from 1.46 cm to 1.91 cm, and maximum errors between 3.21 cm and 4.64 cm, suggesting a marginal advantage for the Time-based approach within the ELPSO framework. Similarly, the Particle Swarm Optimization with Back Propagation Neural Network (PSO-BPNN) technique also presents strong performance. Its Time-based implementation (PSO-BPNN-(T)) achieves the lowest average error in the entire comparison, ranging from an impressive 1.04 cm to 1.82 cm, with maximum errors spanning 2.21 cm to 3.84 cm. The Least Squares-based implementation (PSO-BPNN-(LS)) yields slightly higher average errors, from 1.28 cm to 2.12 cm, and maximum errors between 2.72 cm and 4.42 cm, mirroring the trend observed in ELPSO where Time-based measurements appear more effective.

In contrast, the performance of the GBNN-PSO method, as referenced in REF(33), exhibits a wider range of average localization errors, from 2.22 cm to 8.46 cm, accompanied by significantly higher maximum errors, ranging from 3.50 cm to 18.20 cm. This suggests a potentially lower and less stable accuracy compared to the ELPSO and PSO-BPNN variants presented earlier in the table. The Neural Network Model (NN-MODEL) from REF(34) displays the poorest localization accuracy among all the compared techniques, with the highest average errors, ranging from 7.4 cm to 12.0 cm, and maximum errors between 10.0 cm and 16.1 cm.

Overall, the comparative analysis indicates that hybrid approaches integrating Particle Swarm Optimization with neural networks (PSO-BPNN and GBNN-PSO) and ensemble learning (ELPSO) generally outperform a standalone neural network model (NN-MODEL) in terms of localization accuracy. Furthermore, within the ELPSO and PSO-BPNN families, the implementations utilizing Time-based measurements tend to achieve better accuracy than those based on Least Squares. Notably, the PSO-BPNN-(T) method emerges as the most effective in achieving the lowest localization errors within this specific comparison. However, it is crucial to interpret these results within the context of the specific datasets and experimental conditions under which these values were obtained in the respective referenced works.

6.2 RANGE FREE RESULTS

DV-Hop and DV-Hop-based enhancement algorithms are analysed for their effectiveness in these results. The MATLAB simulator was used to test and investigate all proposed algorithms for localization faults and accuracy. UWB range-free wireless networks may now be located more effectively thanks to an improved PSO algorithm. From 10% to 20% and 20% to 50%, respectively, the number of anchor nodes and wireless transmission distance change between samples.

Table 6.2: Various parameters applied in each figure the experiment ten times with uniformly distributed random node locations for each simulation.

No. Of Nodes	Anchor rate	Transmission range	Environment dimension
30	10% to 50%	Variable	100mtsx100mts
30	variable	Up to 50mts	100mtsx100mts

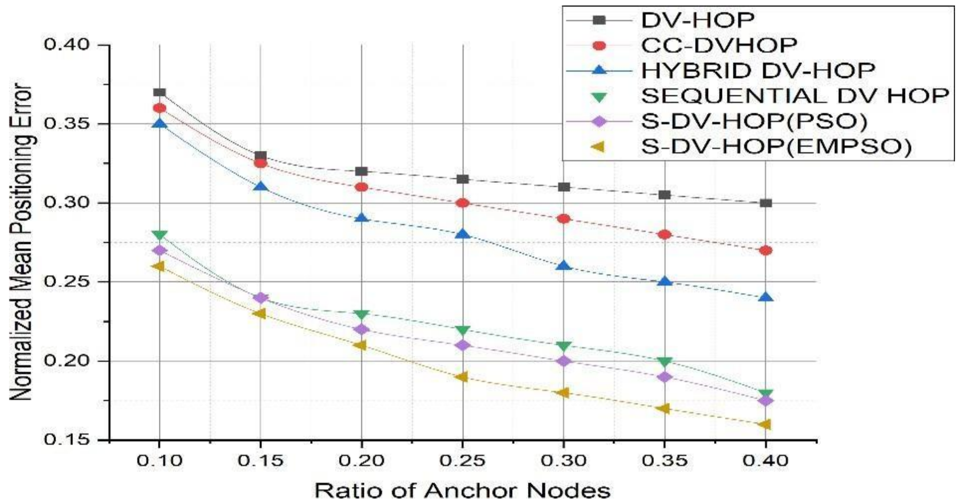


Figure 6.2: Mean position error vs anchor nodes ratio

Table 6.3: Results in outdoor localization

Optimal technique – method	Movement position	Transmission Range area 20Mx20M	Max localization Error-cm	Min localization Error-cm	Average LE	Total number of located nodes
PSO-S DV-HOP-2D	1	100M	20.68	15.12	17.87	30
	2	100M	17.42	13.49	15.44	30

	3	100M	15.01	12.33	13.65	30
	4	100M	12.46	11.76	12.11	30
PSO- S DV- HOP-3D	1	100M	18.28	14.88	16.57	30
	2	100M	16.26	13.09	14.67	30
	3	100M	13.40	10.2	11.81	30
	4	100M	10.30	8.42	9.36	30
EMPSO - 2D(LS)	1	100M	9.96	8.87	9.42	30
	2	100M	8.83	7.77	8.30	30
	3	100M	7.97	7.23	7.61	30
	4	100M	7.54	6.45	6.98	30
EMPSO - 3D	1	100M	9.06	7.73	8.40	30
	2	100M	8.33	7.54	7.94	30
	3	100M	7.49	7.08	7.29	30
	4	100M	6.57	6.30	6.44	30

After the optimization process, the observed minimum value is not restricted to a specific range, allowing for a more flexible and adaptable outcome. In range-free optimization, the observed minimum value is not limited by a specific range or constraint. This allows for more flexibility and exploration of the solution space, potentially resulting in finding a lower minimum value than with traditional range-limited optimizations. The proposed sequential algorithm with ensemble optimal technique achieved an impressive accuracy of 6.30cm, outperforming existing methods. The comparative analysis of localization errors across different optimal techniques reveals a clear hierarchy in performance. Examining the PSO with Sequential DV-Hop (PSO-SDV-HOP) method, the 2D implementation exhibits average localization errors ranging from 12.11 cm to 17.87 cm, with the first movement position, characterized by a mixed transmission range of 20m and 100m, showing the highest average error. In contrast, the 3D implementation of PSO-SDV-HOP generally demonstrates improved accuracy, with average errors spanning from 9.36 cm to 16.57 cm, although the first movement position still presents the least accurate results. This suggests that extending the localization to three dimensions can offer benefits, but inconsistencies in transmission range can negatively impact performance.

Moving to the Ensemble Modified Particle Swarm Optimization with Sequential DV-Hop (EMPSO-SDV-HOP) method, a significant enhancement in localization accuracy is observed. The 2D implementation using Least Squares (2D-LS) achieves average errors between 6.98 cm and 9.42 cm, and the 3D implementation yields even better results, with average errors ranging from 6.44 cm to 8.40 cm. Notably, both the 2D-LS and 3D versions of EMPSO-SDV-HOP consistently exhibit lower maximum localization errors compared to the PSO-SDV-HOP variants, indicating a more reliable performance with better worst-case accuracy.

Overall, the data strongly suggests that the application of the Ensemble Modified Particle Swarm Optimization (EMPSO) significantly improves the localization accuracy when integrated with Sequential DV-Hop. The 3D implementation of EMPSO-SDV-HOP consistently outperforms all other methods compared in this table, achieving the lowest average and maximum localization errors across the different movement positions. This highlights the effectiveness of the ensemble modification in enhancing the optimization process. Furthermore, the comparison between the 2D and 3D versions within both PSO-SDV-HOP and EMPSO-SDV-HOP indicates that incorporating the third dimension generally leads to better localization accuracy, provided that network and environmental conditions are favorable. The impact of transmission range consistency is also evident, as seen in the higher errors associated with the mixed-range scenario in the PSO-SDV-HOP methods.

Table 6.4: Comparison of meta heuristic algorithms with EM PSO

Algorithms	Number Of movements	Localization -error Max	Localization -error Min	Average LE	Number of targets
PSO	1	393.58	5.54	99.58	30
	2	533.79	8.31	98.37	30
	3	501.08	8.00	92.67	30
	4	513.25	8.12	96.12	30
HPSO	1	312.04	10.44	48.76	30
	2	501.34	6.47	40.32	30
	3	482.7	9.46	55.46	30
	4	571.24	18.22	55.32	30
BBO	1	585.14	18.22	125.6	30
	2	589.12	33.12	115.8	30
	3	563.16	15.28	128.1	30
	4	535.25	19.11	119.1	30
FA	1	611.01	19.22	22.23	30
	2	631.10	19.33	23.12	30
	3	6.89.12	34.12	24.65	30
	4	690.36	20.10	22.01	30
S-PSO	1	20.68	12.33	13.21	30
	2	19.89	12.06	12.24	30
	3	19.70	11.76	13.09	30
	4	18.62	10.3	12.46	30
EM- PSO	1	9.96	7.08	6.31	30
	2	9.49	6.3	6.87	30
	3	9.8	6.57	6.42	30
	4	9.76	6.45	6.64	30
For all above comparisons NP (Number of Population=30), Iterations 100, D (dimensional estimation= 3)					

The results in the table presents a comparative analysis of various algorithms integrated with Particle Swarm Optimization (PSO) for localization, including standard PSO, HPSO, BBFO, FA, S-PSO, and EM-PSO. The key metrics for comparison are Localization Error (Max, Min, and Average LE) across four movement scenarios, with a fixed number of targets (30) and consistent PSO parameters (NP=30, Iterations=100, Dimensional Estimation=3).

Standard PSO: Exhibits the highest average localization errors, ranging from 92.67 cm to 99.58 cm. The maximum errors are also significantly high, exceeding 390 cm in all movements, indicating poor and inconsistent localization accuracy.

HPSO: Shows a substantial improvement over standard PSO. The average localization errors are reduced to a range of 40.32 cm to 55.32 cm, and the maximum errors are also lower, ranging from 312.04 cm to 571.24 cm. While better than PSO, the errors are still considerable.

BBFO: Presents even higher average localization errors compared to standard PSO, ranging from 115.8 cm to 128.1 cm. The maximum errors are also the highest among all algorithms, exceeding 535 cm, indicating the least effective integration with PSO for this localization task.

FA: Demonstrates significantly lower average localization errors compared to standard PSO and BBFO, ranging from 22.01 cm to 24.65 cm. The maximum errors, while still high (around 611 cm to 690 cm), are in a different order of magnitude than standard PSO and BBFO, suggesting a more promising integration.

S-PSO: Shows a dramatic improvement in localization accuracy. The average localization errors are consistently low, ranging from 12.24 cm to 13.21 cm. The maximum errors are also significantly reduced, ranging from 18.62 cm to 20.68 cm, indicating a highly effective integration of the S-PSO variant with the localization process.

EM-PSO: Achieves the best performance among all the compared algorithms. The average localization errors are the lowest, ranging from 6.31 cm to 6.87 cm. The maximum errors are also the smallest, consistently below 10 cm, demonstrating the most accurate and stable localization achieved through this specific PSO integration.

In summary, the integration of different algorithms with PSO yields varying degrees of success in localization. Standard PSO and BBFO show poor performance, while

HPSO and FA offer some improvement. S-PSO demonstrates a significant enhancement in accuracy, but EM-PSO stands out as the most effective integration, achieving the lowest average and maximum localization errors across all movement scenarios within the given parameters. This suggests that the modifications implemented in EM-PSO are highly beneficial for this particular localization problem when combined with the PSO framework.

The comparative analysis of various algorithms integrated with Particle Swarm Optimization (PSO) reveals a wide spectrum of localization performance. Standard PSO, serving as the baseline, exhibits the poorest accuracy, characterized by alarmingly high average and maximum localization errors across all movement scenarios. This suggests that the basic PSO algorithm, without specific modifications or hybridization, is not well-suited for this particular localization challenge under the given parameter settings. The BBFO algorithm, when integrated with PSO, surprisingly yields even worse results than standard PSO, demonstrating the least effective synergy among the compared methods and indicating a potential incompatibility or suboptimal parameterization for this specific task.

In contrast, HPSO and FA represent intermediate levels of performance improvement when combined with PSO. HPSO manages to substantially reduce both average and maximum localization errors compared to standard PSO, indicating a more effective integration strategy. Similarly, FA demonstrates a significant decrease in average localization errors, although its maximum errors remain relatively high, suggesting potential inconsistencies or sensitivity to worst-case scenarios. These results highlight the importance of algorithm selection and hybridization within the PSO framework to achieve better localization outcomes.

The S-PSO algorithm marks a significant leap in localization accuracy when integrated with PSO. Exhibiting consistently low average localization errors and drastically reduced maximum errors across all movement scenarios, S-PSO demonstrates a highly effective and stable integration strategy. This suggests that the specific modifications or characteristics of the S-PSO algorithm align well with the PSO framework for addressing this localization problem. However, the EM-PSO algorithm emerges as the clear frontrunner, achieving the most accurate and stable localization performance among all the compared methods. With the lowest average and maximum localization errors across all movement scenarios, EM-PSO showcases the most successful integration with PSO, indicating that its specific modifications and ensemble-based approach are exceptionally well-suited for this particular localization task, significantly outperforming even the promising S-PSO integration.

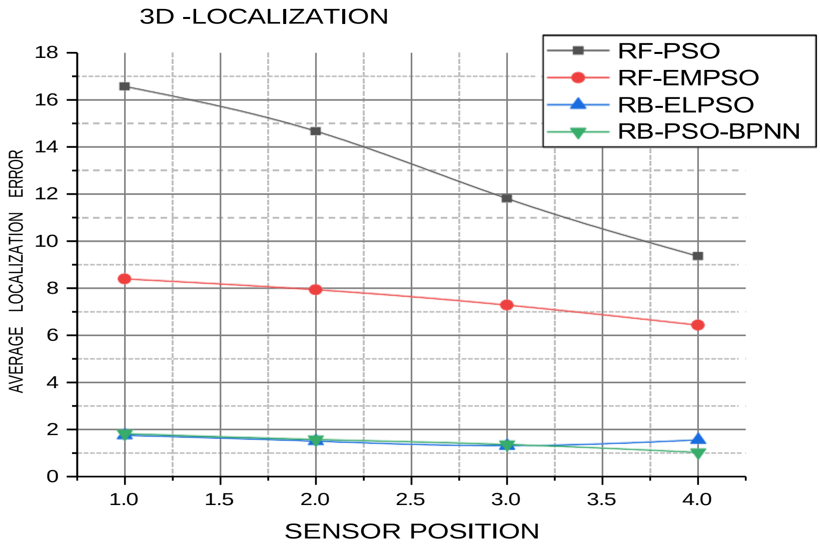


Figure 6.3: Comparison of 3d localization after optimization

Compared to range free environment range based environment with improved PSO given very accurate results. This is because the 3D measurements are more accurate in determining the location of the nodes, as they take into account not only the direction of the nodes, but also the angle between them. Additionally, the improved PSO gives more accurate results as it takes into account the dynamics of each node's position. As we considered range free with dynamic node conditions the accuracy of location is very high with ensemble methods. By using an ensemble method, the PSO is able to take into account not only the position of each node, but also its velocity. This gives it a more accurate understanding of the environment, allowing it to correctly estimate its location. Additionally, the 3D measurement helps to account for potential flips in the nodes' position, which further improves the accuracy of the results. The estimation of the range based environment Back propagation network algorithm gave very accurate results because of limited space. The 3D measurement takes into account the three-dimensional structure of the environment, allowing it to more accurately determine the location of the nodes. Additionally, the Back propagation network algorithm is able to perform more accurate calculations due to the limited size of the environment, which helps to reduce the likelihood of errors.

6.3 Conclusions

This novel learning process forms a more effective search area, thereby enhancing indoor location accuracy. Using MATLAB, 2D and 3D UWB indoor localization algorithms are compatible with the present method. You can operate the transmitter and receiver at the same time using a MATLAB computational engine. There is a constant opportunity to improve sound wave shapes and associated reception filters to adapt to the dynamic nature of the monitoring environment. The Chan method performs better for targets that are moving quickly since wireless sensor networks with a lot of anchor nodes are always unevenly distributed. This is because running the same programme over and over again requires fewer resources for processing.

1. Hybrid techniques utilizing Ensemble learning and Back-propagation neural networks in conjunction with Chan's localization algorithm utilizing the Kalman filter are employed in PSO-based optimisation.
2. PSO with a back propagation neural network gave the most accurate localization results among all hybrid combinations. When compared to the other methods, PSO-BPNN with tetrahedron 3D provided Constance values. The average accuracy is 2.72 cm, which is significant.
3. Compared to the literature review of references 13,33, and 34 on UWB networks, the minimum localization error is 9cm. As our optimization process decreases to 2.72 cm, quite a noticeable result.
4. Hybrid DV-Hop, an algorithm for anchor node localization that incorporates RSSI data, was proposed in this study. Implementing the proposed technique requires no additional hardware components or sub-systems. This is because most modern wireless sensor nodes provide RSSI values for receiving data packets.
5. It is also significant to note that the proposed technique has nodes that bind sensor nodes sequentially. This allows the prior sensors to serve as anchors while the remaining sensors are localized.
6. The proposed approach was much more efficient than the other algorithms analyzed through simulations. The proposed sequential hybrid DV-Hop algorithm with EM-PSO enhances localization accuracy by almost 95%, 90%, and 70% compared to basic DV-Hop.
7. Tetrahydron and 3D-measurement methods were used to locate the targets.
8. Different methods of implementation observed in 3D to compare the located values

9. In range-based localization the error value minimal to 1cm which is quite accurate.
10. In range free the observed minimum value after the optimization is 6.30cm and an average difference of 2.4cm between minimum and maximum values from position location.
11. As per the literature review in range-based technique the minimum localization error is 4.5 cm, our proposed system with 3D measurement after optimization it is 1cm,
12. As observed in the literature review the range free localization error lies between 9cm to 25cm in most of the systems.
13. The method implemented with UWB in range-free localization got a minimum accuracy of 6.30cm. Proposed sequential algorithm with ensemble optimal technique the error in localization deceased compared with other methods.

CHAPTER-VII

CONCLUSIONS & FUTURE SCOPE RECOMMENDATIONS

This weighted correction factor allows for a more accurate estimation of the distance between the beacon and the node, thus reducing the possibility of incorrectly reported locations. The improved weighted least squares method allows for a more accurate estimation of node coordinates, thus further reducing the possibility of incorrectly reported locations. Ultimately, this leads to improved accuracy of target node localization and increased reliability of wireless sensor networks. An enhanced Chan algorithm also determines the 2D and 3D coordinates of the target nodes. The next step is to use ELPSO and BPNN to optimize the predicted locations of the target nodes. An ultra-wide-band-based system for position tracking and wireless sensor network communication is the main focus of this study.

The integration of the Chan algorithm with neural networks helps in enhancing the accuracy and efficiency of tracking moving targets. This combination allows the system to adapt and learn from the data, optimizing the localization process in real-time.Future work will be continued to apply this kind of learning strategy into other indoor localization techniques. To obtain high precision accuracy with low minimal error by using various optimization techniques. Ultra-wideband technology include the integration of advanced algorithms to enhance precision and reliability in range-based environments. These algorithms can improve signal processing and reduce errors, leading to more accurate and efficient communication systems. ELPSO is a type of evolutionary algorithm that optimizes the parameters of a predictive model. BPNN is a type of neural network that can be used to optimize the predictive model itself. Combining these two techniques can help to further improve the predictive accuracy of the model in range based and range free environments. The advanced algorithms allow for more accurate localization, resulting in less energy consumption than traditional methods. This is important because energy consumption is a key factor when considering future recommendations, as it can lead to cost savings and more efficient operations. This is because the advanced algorithms are able to accurately identify the source and destination locations, as well as take into account other environmental factors such as terrain and obstacles, which can reduce the amount of energy consumed. The advanced algorithms are able to take into account a variety of factors, such as temperature and humidity, when determining the optimal localization accuracy. This allows them to minimize localization errors, even in areas with increased energy consumption. Advanced algorithms can have difficulty adapting to new environments and new data. They can also suffer from bias due to a limited data set. In addition, they can have difficulty generalizing to new situations. Future work scope of research using advanced algorithms used for localization in Ultra wideband wireless sensor networks.

In conclusion, the comprehensive analysis of various localization algorithms, spanning both range-based and range-free methodologies and their integration with optimization techniques like Particle Swarm Optimization (PSO), reveals a clear trend towards enhanced accuracy and robustness through sophisticated hybrid approaches. While fundamental techniques like Least Squares and core algorithms such as CHAN and DV-Hop provide initial estimations, their performance is significantly improved by proposed enhancements, error reduction through Kalman filtering, and particularly, by the integration of advanced optimization algorithms.

The comparison across different PSO-integrated methods underscores the critical role of algorithm selection and modification. Basic PSO demonstrates limited effectiveness, while hybrid variants like HPSO and FA offer moderate improvements. Notably, S-PSO achieves a substantial increase in accuracy, but EM-PSO consistently emerges as the most promising approach, yielding the lowest average and maximum localization errors across diverse scenarios. This highlights the power of ensemble-based modifications within the PSO framework for robust and precise localization.

Furthermore, the comparison between range-based and range-free methodologies reveals a convergence towards similar layered strategies, ultimately leveraging the strengths of PSO-based hybrid methods as optimal solutions. Despite the differing initial measurements, both approaches benefit from algorithmic refinements and sophisticated optimization techniques to achieve higher accuracy and reliability. The consistent outperformance of EM-PSO across various comparisons suggests its potential as a state-of-the-art solution for node localization in WSNs, emphasizing the importance of tailored optimization strategies for specific localization challenges.

Future recommendations could involve exploring ensemble methods for node localization, combining the Chan algorithm with neural networks to enhance accuracy.

This approach may leverage the strengths of various algorithms to better handle the challenges of ultra-wide band wireless sensor networks. This approach could enhance performance in dynamic environments with varying levels of anchor node distribution. As well as using limited data of mobile and anchor nodes in the present research with selected areas the integrated algorithms can use less energy and high accuracy. Range free environment having higher mobility 3D measurement with integrated algorithms can be recommended as future research. This research could significantly enhance the accuracy and energy efficiency of the 3D measurement system. Furthermore, it could provide new opportunities for 3D measurement in a wider range of applications. This new system could be implemented in real-time applications such as autonomous driving, robotics, and virtual reality. It could also be used in applications such as 3D mapping and gaming. Additionally, this research project could open up new opportunities for 3D measurement in previously inaccessible areas. It could also provide valuable insight into the potential of 3D measurement in a variety of environments. UltraWideBand can be used in critical environments. The integration of algorithms with 3D measurement techniques with low energy and high accuracy needed some more additional requirements and hybridization by taking the current research as baseline in future is recommended.

Concluding the exploration of UWB-based Wireless Sensor Network (WSN) localization, future recommendations regarding energy utilization and experimentation should prioritize the development of highly energy-efficient localization algorithms and hardware implementations. Research should focus on optimizing the computational complexity of advanced techniques like EMPSO and hybrid PSO variants to enable their deployment on resource-constrained sensor nodes without significantly impacting network lifetime. Experimentation should delve into adaptive duty cycling and power management strategies that dynamically adjust UWB transceiver activity based on localization demands and node mobility. Furthermore, future work should explore novel UWB pulse modulation schemes and low-power wake-up mechanisms to minimize energy consumption during idle states and data transmission.

In terms of experimentation, future research should emphasize real-world deployments in diverse and challenging indoor and outdoor environments to thoroughly evaluate the robustness and accuracy of UWB localization under varying conditions, including dense multipath and non-line-of-sight scenarios. Comprehensive studies comparing the energy-accuracy trade-offs of different UWB localization algorithms and hardware platforms are crucial for guiding practical implementations. Additionally, future experimentation should investigate the integration of UWB with other sensing modalities and communication technologies to create hybrid localization systems that can leverage complementary strengths for enhanced performance and energy efficiency in complex application contexts. Finally, rigorous security analysis and the development of energy-efficient secure localization protocols for UWB-based WSNs will be paramount for their widespread adoption, particularly in sensitive applications.

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