IMPLICATIONS OF METAHEURISTIC APPROACHES IN OPTIMUM LOCALIZATION OF STATIC AND DYNAMIC WSN's

Thesis Submitted For the Award of the Degree of

DOCTOR OF PHILOSOPHY

in

Electronics and Communication Engineering

By

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DECLARATION

I hereby certify that the work that is being presented in the thesis entitled **"Implications of Metaheuristic approaches in optimum localization of Static and Dynamic WSN's"** submitted to the Department of Research at Lovely Professional University, Phagwara is an authentic record of my work carried out during a period from August 2018 to July 2022 under the supervision of Dr. Manwinder Singh, Professor and Dr. Parulpreet Singh, Assistant Professor, Lovely Professional University. The matter presented in this thesis has not been submitted to any other University/Institute for the award of a PhD degree.

Signature of the Candidate:

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Date: 13/07/2022

Place: Phagwara

CERTIFICATE

This is to certify that the thesis entitled **“Implications of Metaheuristic approaches in optimum localization of Static and Dynamic WSN’s”**, which is being submitted by Mr. Gagandeep Singh Walia for the award of the degree of Doctor of Philosophy in Electronics and Communication Engineering from the Faculty of Technology and Sciences, Lovely Professional University, Punjab, India, is entirely based on the work carried out by him under our supervision and guidance. The work reported embodies the original work of the candidate and has not been submitted to any other university or institution for the award of any degree or diploma, according to the best of our knowledge.

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ABSTRACT

Wireless Sensor Network (WSN) is comprised of a number of sensor nodes that acquire and transmit data wirelessly. In the majority of WSN applications, including health monitoring, military, environmental sensing, rescue, and biological tracking, sensor node position is significant. Localization is the process of determining the location value and placement of sensor nodes. While going through the literature, localization techniques that enable localization processes are characterized by sets of pairings, such as static and dynamic localization, centralized and distributed localization, outdoor and indoor localization, Two-Dimensional (2D) and Three-Dimensional (3D) localization, etc. In various circumstances, the primary objective of these localization systems is to determine the relative coordinates of the node where an event is occurring.

WSNs are advantageous for a variety of military and commercial applications due to their quick deployment, self-organization, and fault tolerance. In recent years, mobility has emerged as an important research topic for WSNs. In static localization, the location of the target node may be calculated during initialization only. In a mobile context, however, the assessment of target node location is an ongoing process. Such mobile situations demand more time, energy, and the availability of a quick localization solution. When network mobility is taken into account, the localization procedure is filled with several problems and obstacles. Additionally, the dynamic localization process may be separated into three categories: mobile targets and fixed anchors, mobile anchors and fixed targets, and both mobile targets and anchors. In mobile settings, periodic re evaluation of target node placements is required because node positions shift frequently.

In the first contribution of the thesis, a novel concept of **2D range-based localization with target mobility is proposed by** introducing virtual anchors to locate mobile target nodes in a two-dimensional scenario using various meta-heuristics approaches. The novel proposed algorithm, the Dragonfly-Firefly (DA) meta-heuristic, is implemented for 2D WSNs. To locate unknown nodes, only one

anchor is used. A node whose position is known is normally deployed in the middle of the region that is to be sensed. To begin, the anchor and the target node distance are calculated after the notion of VN's is proposed, with VN's placed at certain angles in the field at a defined distance between the anchor and the target node. The centroid is calculated, and DA is used to compute the localization error. Similarly, one more approach has been proposed in a similar fashion and environment. An algorithm known as the Neural Network Algorithm (NNA) is being proposed for computing the location of randomly moving target nodes. To improve the findings, hybrid optimization strategies can be applied in the future.

In the second contribution of the thesis, a concept of **3D range-based localization with target mobility is proposed, which is** based on various meta-heuristics for moving target nodes using one anchor node. In a simulation-based scenario, the middle and lower levels include nodes with uncertain positions, whereas the top layer has a single anchor node. The Adaptive Plant Propagation Algorithm (APPA), a revolutionary soft computing approach, is presented here to determine the optimal placements of these mobile nodes. These nodes are diverse and have been deployed in an asymmetrical environment with a DOI value of 0.01. Simulation findings demonstrate that the proposed APPA method surpasses previous meta-heuristic optimization strategies in respect of localization error, computational time, and localization determination. With the help of the results, it has been inferred that APPA is better than other algorithms at finding accurate locations and has faster convergence.

Further, third contribution of the thesis is the development of **3D range free localization with target mobility.** In the proposed algorithm, only single anchor node has been used for localization and there is no requirement of the complex hardware to get the distance information between anchor and target node. In an anisotropic environment, target nodes and anchor nodes are distributed across the borders of three layers. Anchor nodes are placed in the top layer, while target nodes are scattered in the middle and bottom levels. A fuzzy Logic System (FLS) has been used for the modelling of RSS and edge weight to reduce computational complexity. Further, the

Tunicate Swarm Naked Mole Rat Algorithm (TSNMRA) is used to optimize the membership function bases of RSS and edge weights in order to reduce the position error. Even though this mobility-based approach is presented for the first time, simulation results indicate that the proposed technique achieves greater localization precision than static range-free schemes. As per the simulation results, the RF-TSNMRA approach has greater localization accuracy than other methods in the literature, such as the weighted centroid method and the RF-HPSO, RF-BBO, and RF-IWO.

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First and foremost, I want to thank God for the successful completion of my research work and thesis.

The present work was done due to the support and cooperation of many people. I would like to convey my gratitude to my supervisor, Dr. Manwinder Singh and co-supervisor Dr. Parulpreet Singh for their direction, encouragement, and support throughout my research. They guided me in carrying out the research and completing the work in many ways, explaining when necessary, thanks to their enthusiasm, motivation, and encouragement. I would also want to express my gratitude for their efforts, which inspired me to widen my research to include a variety of views. It would be difficult to accomplish this study without their foresight.

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Gagandeep Singh Walia

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Sr. no.	Title of paper with author names	Name of journal / conference	Published date	Issn no/ vol no, issue no	Indexing in Scopus/ Web of Science/UGC-CARE list (*please mention*)
1.	Three Dimensional Optimum Node Localization in Dynamic Wireless Sensor Networks	Tech Science Press, Computer Materials and Continua, IF-3.8	04-05-2021	70,1	Web of Science
2.	Localizing Mobile Nodes in WSNs using Dragonfly Algorithm	International Conference on Computing Sciences (ICCS)	02-06-2022	1	Scopus
3.	Localizing Mobile Nodes in WSNs using Neural Network Algorithm	International Conference on Advancements in Nanoelectronics and Communication Technology	24-06-2022	1	Scopus

CHAPTER -1

INTRODUCTION

This chapter is dedicated to the Wireless Sensor Networks (WSNs), their architecture, features, applications, localization in WSN, and the associated challenges. We also conduct the study of localization approaches covered by the range-based and range-free category against their merits and demerits and the various metrics used to evaluate the localization.

1.1 WIRELESS SENSOR NETWORKS

WSNs are generally grouped into battery-operated units that are networked to process, control, collect and communicate data to the users. These devices are termed motes/sensor nodes. WSNs comprise nodes placed within a particular target area or application-based target [1]. An array of such motes deployed in a particular area (indoor or outdoor) for assimilating respective purposes form WSN. The initial advancement of WSN was inspired by military applications, such as surveillance on the battlefield and detection of the enemy. As years passed by, significant measures of research endeavors have empowered the actual execution, and as a result, WSNs have become important tool for many real-life applications, viz. agriculture, greenhouse, disaster relief, target tracking, monitoring, etc. The benefits offered by WSN in comparison with wired network are less cabling, mobility, less installation cost, automation in the factories, smart infrastructure, etc.

One of the types of WSN is underground WSN, where the sensor nodes are placed under the ground to monitor various actions [2]. Underwater WSN uses fewer sensor nodes, which are expensive and uses sparse placement. The benefits offered by WSN in comparison with wired network are less cabling, mobility, less installation cost, automation in the factories, smart infrastructure, etc.

In WSN, each node in a network has the capability of Sensing, data gathering, processing the data, and communicating to the neighboring node or sink. The sensed data’s frequency, size, and quality are influenced by the physical resources available to the sensor node [3]. Flexibility, economic viability, and energy efficiency are some of the design objectives of the sensor node. As shown in figure 1.1, a sensor node consists of five parts/subsystems as described below.

Sensor:- This subpart of the sensor node is the actual interface of the node with the physical world. Parameters like temperature, pressure and humidity from the physical world can be measured through a sensor.

Processor:- A processor is the cognitive component of a sensor node. This sensor node subcomponent is responsible for processing, code execution, and data collection.

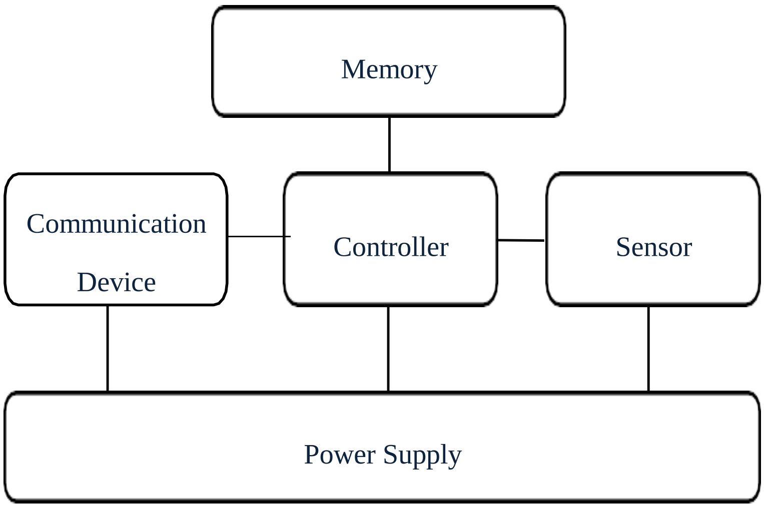


Figure 1.1: WSN node Architecture

Transceiver:- The work of the transceiver subsystem is to communicate with the node within the network and send data from one node to other.

Memory:- The memory subsystem stores data and basic program codes in a sensor node. Appropriate memory size is crucial in a node, as it affects the node's cost and power consumption.

Power Supply:- This subsystem is responsible for supplying energy to the other subsystem in a sensor node. Typically, batteries can be used for supplying energy within the node. These batteries can be recharged or replaced.

1.2 WSN ARCHITECTURE

Figure 1.2 shows the architecture of WSN that consists of sensor nodes, sink node and end user. The vast quantity of sensor nodes is built up as a classic WSN.

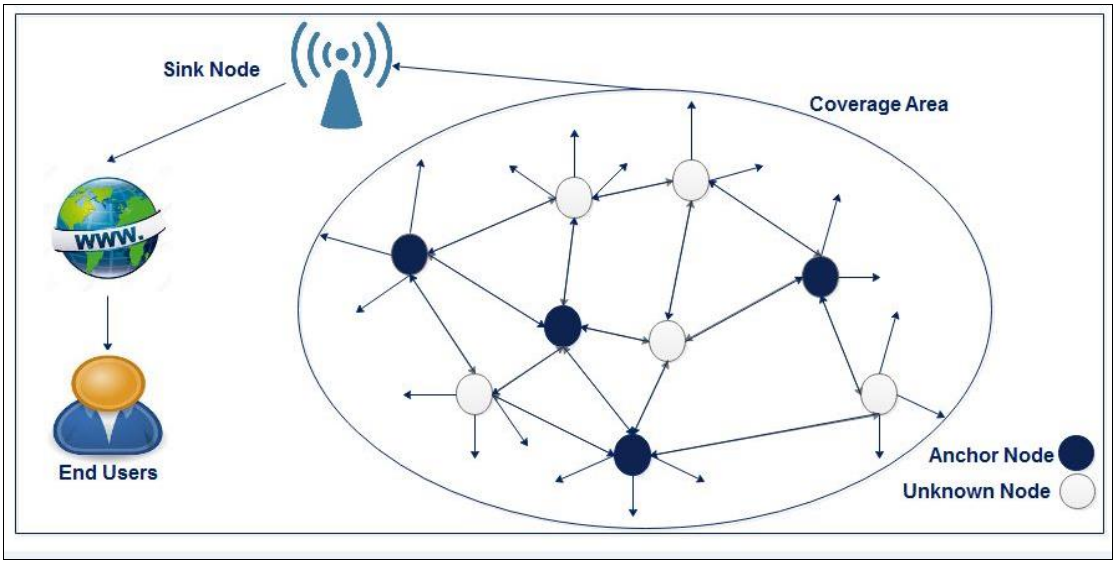


Figure 1.2: Representation of the wireless sensor network

Further, these sensor nodes also comprise various critical components, such as the power required for their operation, a sensor is required to detect the event and to change the sensed data into electrical signals. After that, the data will be sent to the microcontroller, where it is processed in the form of an electrical signal, and the transceiver will receive the data so that the communication can be reached.

1.3 WSN FEATURES

The various features of the WSN are presented as [4-5].

- **Energy Regulation:** In WSN, sensor node has limited power, so energy regulation is necessary to increase the existence of WSN.
- **Communication model:** Sensor node plays a significant role in the communication purpose of the network model. In addition, since large numbers of sensor nodes are densely conveyed, neighbor nodes are near each other to decide system performance.
- **Different Hop Communication:** Long-distance communication requires potent transmission. Thus, intermediate hops are used in WSN to make communication possible over less powerful transmission.
- **Node density:** Node density depicts that all nodes are within the communication range of several other nodes at all times. The node density is an essential factor influencing the connectivity in WSN. It is expected in

sensor network exploration that the node density is sufficiently high to guarantee that all nodes are constantly inside the communication range of a few particular nodes.

- **Self-Organization:** WSN has an important self-organization feature in which the network should be able to tolerate faults and should be able to add more sensor nodes as required.
- **Dynamic-Topology:** As some sensor nodes are removed in WSN due to some battery issues or it may be other faults, the network topology will change. Similarly, according to the requirement, some new sensors are added to the network, and the topology will change again. In this way, WSN has a dynamic topology [6].

1.4 APPLICATION AREAS IN WSNs

WSNs have become popular in solving various problems due to their flexible nature in different domains. It has the potential to change our daily living scenes in many ways. WSNs can be applied in various ways. Different applications of WSN are presented as [7-8].

- **Health monitoring:** WSNs play a vital role in health monitoring. As sensor networks are widely used in the health care area. Some of the health applications are supporting disabled patients, monitoring doctors and patients, telemonitoring human physiological data, controlling drug administration inside the hospital, and various diagnostics in the nursing homes monitoring old patients. This can be done by implanting various sensors in the human body for the detection of muscle activities and neural changes. WSN helps us in the detection of sign monitoring and unconsciousness. It can also be used for measuring and monitoring the physiological signals i.e., glucose level, heart rate and blood pressure.
- **Military Applications:** WSNs are integral to military applications and play an influential role in monitoring border areas for applications like surveillance, earthquake detection, and detection of opponents' unusual activities. WSN enhances the power of the military by being a fundamental part of Military Control, Intelligence, Investigation, Communication, etc. Human intervention in those areas is not easily possible.

- **Weather Testing:** In weather testing, WSN is used to know temperature, rain chances, air-pressures, wind-velocity, and also disaster probability.
- **Environmental Sensing:** WSNs are used to collect meaningful data from various sensor nodes over a while to detect some unwanted changes in the environmental conditions. These unwanted changes could be forest fire detection, landslide detection, climate monitoring, air pollution monitoring, etc.
- **Function Approximation:** When a physical variable, such as temperature or pressure, varies from one site to another, this is known as a location function. To approximate this unknown function, each sensor node collects a number of samples in a network to extract various characteristics and then approximation mapping is done at the sink node.
- **Industrial Applications:** Wireless sensor networks control and monitor various parameters like temperature, viscosity, vibrations and pressure in the industrial field. In the industrial field, the “supply chain, factory and production sector” are mainly influenced and controlled by WSNs.
- **Traffic Monitoring:** WSN is used in traffic system to control the traffic on reading, to control the jams and also reduces the accidents on roads.
- **Security and Surveillance:** The main difference between environmental and security monitoring is that there isn’t any actual collection of data in security monitoring. It keeps monitoring the surrounding data but transmits information only when there is some violation of security measures. The alarm message is the immediate reaction to the violation of the security system. Instant alarm reaction makes the system more reliable [9].
- **Home Monitoring:** WSN has played a substantial role in home automation. It gives our house the ability to think, process and act accordingly. We have turned our houses into smart homes by implementing sensors in every corner. By sensing the environmental conditions, our home will adjust itself accordingly. For e.g., it will sense the temperature and adjust the parameters air conditioner accordingly. The sensors control the lights in the balcony and corridor, which will illuminate themselves according to the intensity of light present there.

As we have seen different paradigms that WSN has brought renaissance in the field of technology and automation. Some of the applications are shown in the following figure 1.3.

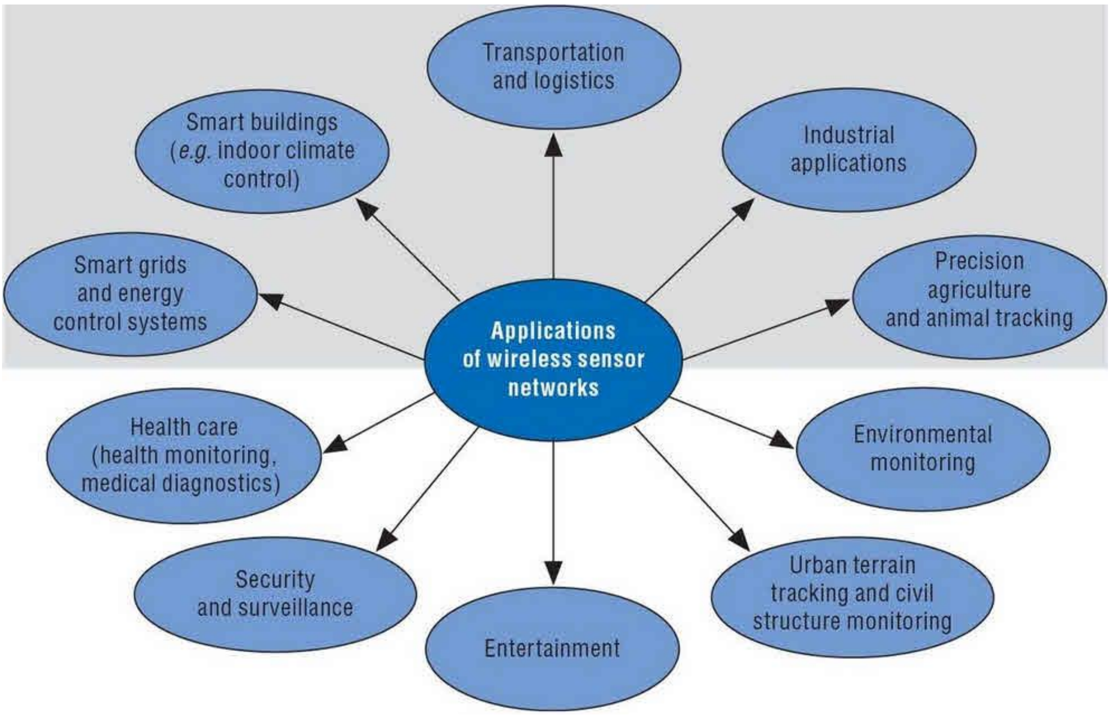


Figure 1.3: Applications of wireless sensor networks

1.5 ISSUES AND CHALLENGES IN WSN

Following are some of the major issues that affect the performance, accuracy and design of WSNs.

- **Energy:** Energy is essential for a sensor node to perform various operations, including data gathering, processing, and communication. Even when the node is idle, it requires some amount of energy. The batteries that provide power to the sensor node need to be recharged or replaced after consumption. Sometimes due to some demographic or geographical conditions, it is challenging to recharge or replace batteries. So, designing an energy-efficient network is a crucial research issue [10].

- **Self-Organization:** As soon as the WSN is deployed, they should be able to perform necessary work without human interference, such as network configuration, maintenance, fault tolerance and localizing themselves [11].
- **Quality of Service (QoS):** It is the level of facility that WSN provides to its user. When WSN works for the user in the real-time application, that time, QoS should be good. Although it is not easy in WSN because the network topology can change at any time, and when the sensors in the network send the collected data, there are chances of unstable traffic affecting the QoS [12].
- **Security:** Confidentiality, authenticity and integrity are essential issues related to a WSNs security. Confidentiality is the essential requirement for data transmission within a network. Also, the integrity and authenticity of data should be maintained in a network, i.e., actual data should reach the receiver [13].
- **Localization:** A WSN's primary role is to control and track activities that can be assimilated meaningfully when their specific positions are identified. Typically, this requires knowledge of the reporting nodes' locations. The localization problem is the challenging task of determining the locations of nodes in a WSN [14].
- **Mobility:** WSN deployments are done in either static or mobile environments. Initially mobility has many challenges that are required to overcome, including energy consumption, connectivity, and coverage [15].
- **Deployment:** Deployment in WSNs is challenging, as it refers to implementing a network in a real-world scenario. In locations where it is hard to reach, the sensor nodes are deployed through helicopters, or some particular topology is used for deployment. Also, several sensor nodes' concurrent transmission attempts result in network congestion in densely deployed networks. So, properly deploying nodes in WSN is a laborious, challenging and tedious task [16].
- **Fault Tolerance:** A network should be capable of adapting to changes in connectivity caused by node failure. The WSN should remain functional even if any node fails. So, selecting an efficient routing algorithm that can change connectivity in node failure is an essential area for further research [17].

1.6 LOCALIZATION IN WSN

Localization is the procedure for defining the location value of the sensor nodes and the positioning of the sensor node [18]. Location computation, confinement methods, and calculations are used to estimate the actual position and area of its deployment, whose actual place was not defined earlier [19]. It is possible only with the help of some nodes whose locations are already predefined. Those actual nodes are named anchor nodes [20-21]. During deployment, manually specifying location data on each node is not a feasible alternative. Similarly, it is impossible to provide every node with a Global Positioning System (GPS) receiver due to high cost and deployment restrictions.

Ultra Wide Band (UWB) approaches are ideally suited for interior use, whereas acoustic transmission-based systems require additional hardware. Both strategies are precise but costly in terms of energy usage and processing. Un-localized nodes calculate their locations via the energy-intensive beacon signals of anchor nodes. Several methods have been developed in the literature to decrease the communication cost. Similarly, if a node incorrectly guesses its position, this inaccuracy propagates throughout the network and to subsequent nodes, resulting in incorrect information regarding the placement of anchor nodes. The position estimate of the target nodes is mainly determined by the RSS/distance between the anchor node (whose position is known) and the target node (with unknown location).

Types of nodes in WSN [9] are Beacon node and Unknown node as described below.

- **Beacon Node/Anchor Node:** These are the nodes that are aware of their position inside a certain target region. These nodes know there position because they are deployed manually, they are attached with Global Positioning System (GPS). These nodes have significant impact on the localization because more anchors give more exactness in location determination.

- **2D and 3D Nodes:** 2D nodes are deployed in XY plane and all the nodes are in the same height whereas in 3D nodes deployment along with XY plane, sensor height is also considered.

1.6.1 Unknown Node/Free Node:

1.6.1 Unknown Node/Free Node: These nodes do not know their position in a particular target area. These nodes use the anchor node information to determine their position. The process of finding the unknown node's position is, in fact, localization.

1.6.2 Issues in context of Localization in WSNs

Many research proposals are proposed for effectively determining a sensor's actual position, but the primary concern is to lower the values of the error occurring during this process. However, some essential open issues which promote consideration and examination to enhance the location computation procedure in sensor systems are as follows:

- **Efficient energy utilization in sensor localization:** Recently, the analysts have featured the proficient energy utilization in location computation of sensor node is defined in [22-25]. However, it is still very difficult to outline energy effective node location calculations framework in WSNs.
- **Localization in 3D WSNs:** The procedure for Three-Dimensional (3D) nodes localization process uses enhanced heuristic technique for node distance calculation. In WSN the complexities factor and the restriction issue has not been looked into the 3D WSNs [26]. As contrasted the Two-Dimensional (2D) WSNs, there are generally few plans for 3D WSNs.
- **Limited Resources:** With the advancements in chip design and fabrication techniques, the sensor nodes are getting smaller and smaller. Thus the resources at their disposal for example, battery power, storage capacity, and processing capability, are getting reduced. The localization method must produce accurate location estimations despite the restricted availability of resources.
- **Mobility:** Traditionally, sensor network is formed using static or immovable nodes. With the need for new applications like IoT, however, the network became mobile. The localization method must be flexible and able to account for the movement of anchors, targets, or both.

- **Secure Localization:** Secure localization has continually been among the critical issues of broadly deployed sensor nodes in WSNs. The security issue of the node location system is getting the researcher's attention to design a robust system as presented in [27-28]. The security issue in localization is vital because data for that particular location is essential to protect that node from malicious attacks.
- **Minimum Number of Beacons:** In wireless sensor network many node localization technique is followed on beacon's node. The location of this special node is determined by GPS or via setting to them at particular recognized coordinates points [19].
- **Obstacles and Irregular Deployment:** The localization procedure is also influenced by the presence of obstructions or an uneven deployment region. The primary premise of WSNs is Line-Of-Sight (LOS) communication between nodes. Obstacles may induce signal diffraction and bending, resulting to faulty estimate and an improper result.
- **Error Propagation in Interferometric Ranging Based Localization:** The extending Technique in Radio Interferometer has been proposed as a possible course of error propagation in the node location estimation process. It has advantages in the position estimation process, which could be profoundly exact over other location techniques like (RSSI), (ToA) and (AoA). This technique has some limitations due to more estimation for readings and is constrained to smaller systems with just 16 nodes. An iterative calculation because of Interferometric to represent bigger systems during location calculation. Because of interferometric ranging, future localization algorithms require a way to diminish the propagation errors as represented in [29-30].
- **Energy efficient and consumption model:** WSNs are an asset on resource constraints in nature. These formulate energy effectiveness during the efficient energy consumption model design as described in [31]. Sensor nodes in WSNs should know their positions with a specific end goal of working together adequately. The sensor node localization information helps people in different application domains in the network.

1.6.3 Localization Procedure

The primary purpose anticipated from a WSN is event reporting; however, the significance and accuracy of an event's assessment cannot be assured until its specific location is verified. In WSN, the localization technique for unknown nodes is separated into three sections [32] as specified in figure 1.4.

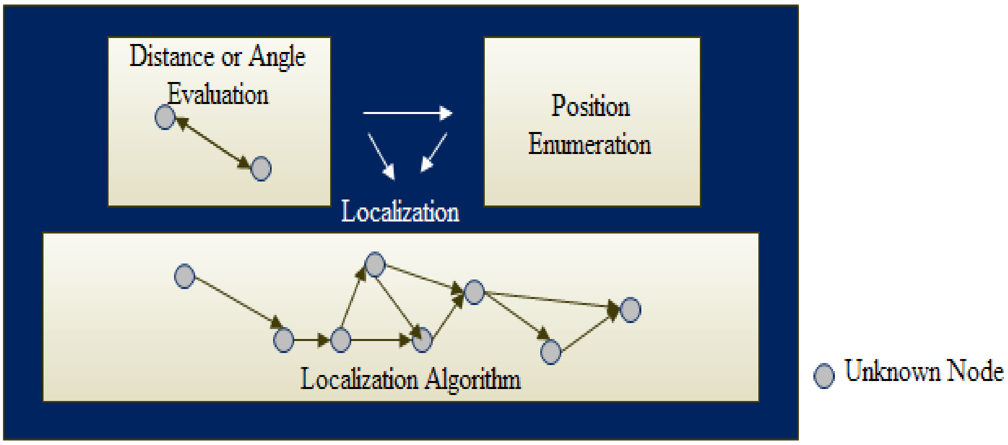


Figure 1.4: Description of localization process

Mainly, localization algorithms consist of two stages: the first stage is used for measuring the distance and the second stage is used for solving the computations.

1.6.3.1 Measurement Stage

In this stage, the distance measured between different nodes is considered an important parameter, including angle measurement and their connectivity between them. These techniques are classified into five main categories described as follows:

1. Strength of the received signal.
2. Arrival of the signal at a particular time or the difference in their arrival times.
3. Angle of arrival.
4. Proximity, based on the network connectivity.
5. Picture/scene analysis.

Each category has been described in some detail manner below.

- **Received Signal Strength Indication (RSSI):** This is used basically to observe the received incoming signal. On the arrival of the received signal, the task of RSSI is to calculate the distance based on the incoming signal. Distance calculations are performed using the received signal strength of the incoming signal [33-34]. Only minimal hardware is needed to calculate the received signal strength, which is one of this method's most significant advantages. But its limitation is that the measured values will change in the case of mobility, environmental conditions, path loss, or fading.

- **ToA:** It finds the distance and time at which the incoming signal is received, as the speed of propagation information is already available. The transmitter and the receiver end are synchronized, and the transmission start time is known. The parameter speed of the light is known and distance calculation is done based on the time of the incoming signal's arrival at the receiver end [35-36]. In this method, synchronization must be required between the transmitter and the receiver clocks for accuracy, which leads to additional hardware requirements at both units, and increases complexity.
- **TDoA**: In this scheme, the medium used for transmission gives a different speed. The arrival of any signal at the receiver end is used to measure the arrival of the other signal. The distance is calculated based on the arrival time of these two transmitted signals. This method provides accuracy under LOS conditions, but if certain disturbances occur in the environmental conditions, it leads to the failure of LOS conditions. Also, with the change in environmental conditions, these arrival times will vary from their actual values, leading to incorrect distance measurements.
- **Angle of Arrival (AoA):** Using the AoA method, the computation between the anchor and the target nodes based on distance is also calculated. In this method, an angle is made between the two lines, where the first line connects the transmitting and receiving ends, and the second line is between the receiver and the other direction, taken as a reference. The distance measured through this technique is more accurate than the distance calculated using the RSSI method mentioned above [37].

- **Proximity:** This is the simplest and cheapest method available for calculating the distance between the nodes because it measures distances only between those nodes which are inter-connected and within range. The hard- ware configuration required is simplest under this scheme [38].

- **Picture Analysis:** This technique behaves differently from the techniques mentioned above. In this, the distance calculations are carried out using a picture or based on scene analysis. In this technique, additional hardware is required, which leads to complexity and is the main drawback of this technique.

1.6.3.2 Measurement Stage

In the second, computational stage, the estimations done on determining the distance and angles in the previous stage are collated for calculating the positions of the unknown nodes. These methods, which work on computational analysis, are discussed as follows.

- **Trilateration**: In this scheme the estimated coordinates of the target node is determined with the help of three anchor nodes, and the location of the tracking nodes is calculated [39]. As shown in Figure 1.5, the determination of the target nodes coordinates is obtained from the coincidence of consecutive circles. Here, the positions of the anchors are represented as x1 and y1 and so on, while x, y denotes unknown node positions and *d* specifies the distances.

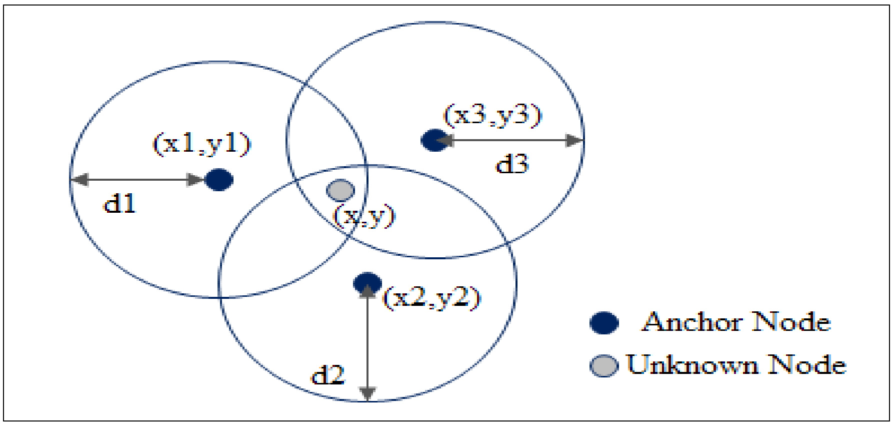


Figure 1.5: Working of trilateration method

- **Triangulation**: Geometrically, the triangulation technique is used to obtain the information of 2-D coordinates on the basis of angles calculated between the nodes and the reference points. Using mathematical sine and cosine rules, the position of the target nodes can be calculated [40]. Figure 1.6 shows this technique that requires at least three anchor nodes.

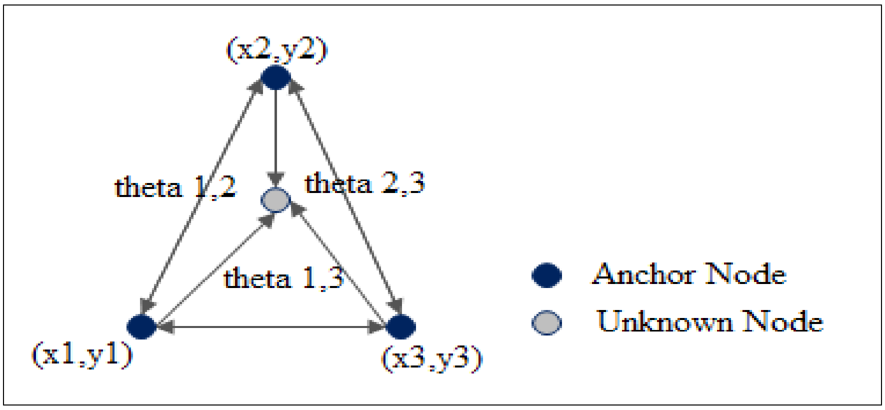


Figure 1.6: Working of triangulation method

- **Multilateration:** In the trilateration approach, the calculated distance is not perfect because the joining of the three circles does not correspond to a single point. In order to cope with this limitation, at least three anchor nodes are required, a process termed multilateration [41]. The results of this technique are much more efficient than those from trilateration. Figure 1.7 represents this concept.

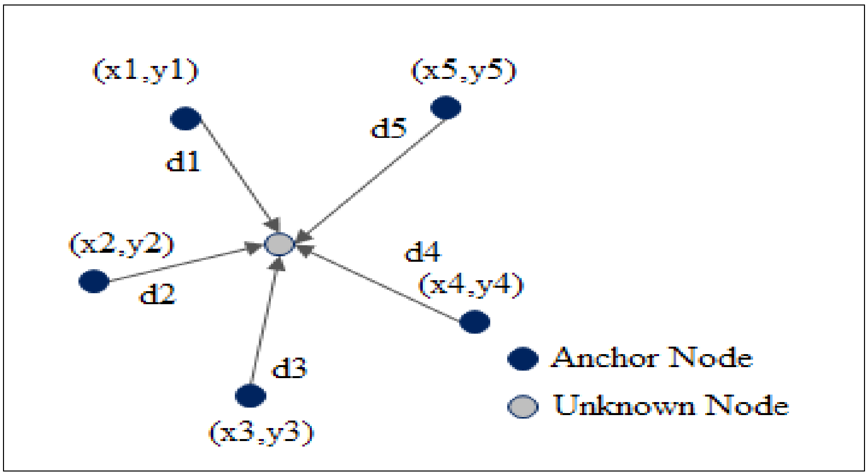


Figure 1.7: Working of multilateration method

1.6.4 Classification of Localization Algorithms

The localization concept is gaining importance in almost all real-world applications of WSNs. The survey of these algorithms provides detailed explanations of the different techniques available for localizing the nodes referred to as anchor-based, anchor-free, range-free and range-based nodes, etc. Every node connected to the network broadcasts a beacon signal processed by the receiver at the reception section to determine the distance, which helps count hops. Figure 1.8 classifies the various available localization algorithms.

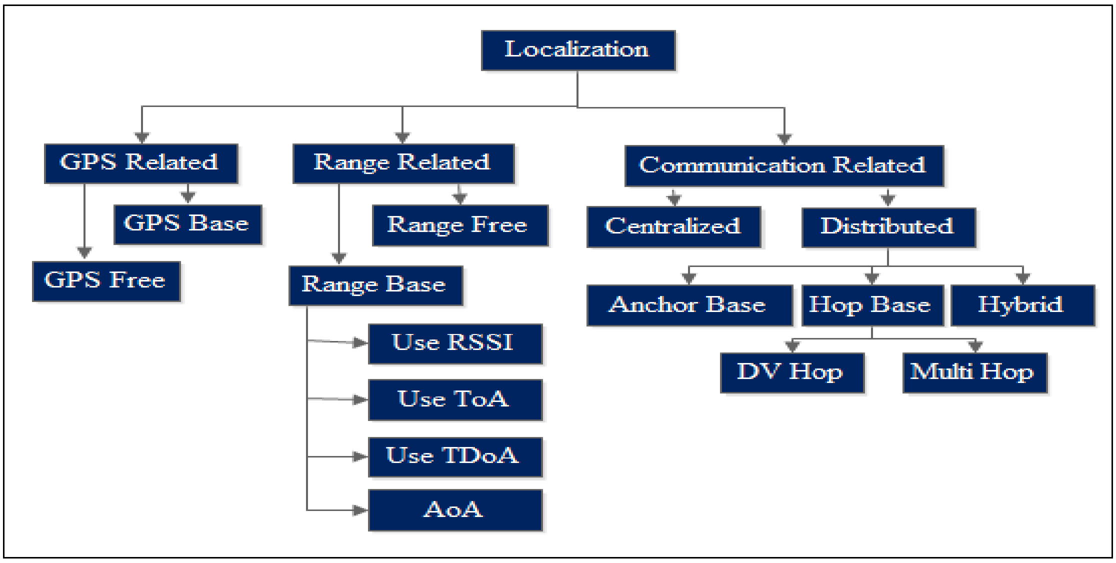


Figure 1.8: Taxonomy of WSN localization methods

1.6.4.1 GPS Related

The different classes of GPS-related approaches are GPS-based and GPS-free ; each one has its own advantages and disadvantages.

- **GPS Based:** In this method, all sensor nodes are equipped with GPS receivers. With GPS, localization accuracy is quite good; but, GPS only communicates in the LOS; in crowded areas, numerous obstructions may affects; and the expense of equipping all sensor nodes with GPS puts this method prohibitively expensive.
- **GPS Free:** To overcome the constraints of a GPS-based strategy, instead of connecting every sensor node with GPS, connect just a subset of sensor nodes

with GPS. These nodes transform into anchor nodes. Then, unknown nodes utilize the anchor nodes to locate themselves using any range-based or range-free localization technique.

1.6.4.2 Range Related

The location determination algorithm is of two types, namely range-free and range-based techniques. Triangulation, trilateration, and multilateration are used for identifying a position utilizing a range-oriented methodology.

- **Range Based (RB):** In RB localization techniques, the anchor node's range information is required, but, in the second method, information relevant to the range is not required. Using specialized hardware, the distances between the nodes are calculated precisely. The main issue arising from this technique is accuracy degradation taking place in the case of mobility scenarios and of various noises taking place in the environment.

- **Range Free:** A network formation in the case of the range-free technique is the one in which a direct relation between the hop count and distance is formed. In this case, the locations are calculated using radio connectivity information among their available neighboring nodes. This technique is more efficient, in terms of simplicity and cost- effectiveness, than the range-based localization techniques. Several approaches related to range-free techniques are given below [42-43].

1.6.4.3 Anchor Related

This defines whether the localization algorithm is using the anchor node or not. These are the techniques available on which the position of target nodes is relied upon. Using (anchor-based) method, the information about the anchor node is required in order to determine the unknown node coordinates in contrast; anchor-free procedures do not need such knowledge about the anchor. In the deployment stage the position of a few nodes, known as anchor nodes, are known, as they include a GPS feature, whereas, in the case of the anchor-free method, localization is achieved, using the information of the relative coordinates [44-45].

- **Anchor Based:** The main motive behind the use of the anchor-based method is the calculation of the distance from the unknown nodes to the known nodes; after the calculation on this basis is carried out between them, then, by using localization algorithms, the unknown node deter- mines its coordinates in space, as, for determining 2-D coordinates, three anchor nodes are at least required and, for determining 3-D coordinates, four anchor nodes at least are required.
- **Anchor Free:** In cases where no anchor node is available, there are two important steps to be followed for determining or localizing the unknown nodes. By the use of different localization methods available, every node in the sensing field computes the distance between them and their neighboring nodes. Then, using distance information, every node deployed in any region of interest determines its coordinates itself.

1.6.4.4 Computation Based

It specifies if it is a centralized or decentralized algorithm. Both centralized and decentralized algorithm design methods are distinct.

- **Centralized:** A central processor is responsible for computing all the computations by the centralized method. The main advantage of using the centralized method is that each node does not need to perform the computations. The main limitation of using this technique is that every node sends the data back to the base station. Simulated annealing and RSSI-based localization come under the classification of centralized localization algorithms. These algorithms are better in terms of localization accuracy because complete information about the connectivity and distance is available between the deployed sensor nodes and their neighbors [46].
- **Distributed:** In the case of distributed localization algorithms, the sensors deployed in the field compute the required information in terms of either connectivity or distance on an individual basis. In this method, each node communicates with them or with their neighbors in order to determine their own location. Beacon-based, coordinate system-based and hybrid localizations

are categorized under distributed localization algorithms. In this method, much iteration is required to achieve stability, resulting in the technique being a little slow, which leads to a drawback of this method [47].

1.6.4.5 Mobility Based

In the static algorithms, once the nodes are deployed they will not move; but in dynamic method deployed sensor nodes have some mobility and will move accordingly [48–50].

- **Static:** In static algorithms, the coordinates of unknown nodes are determined during the set-up of static WSNs. In static algorithms, the convergence rate is fast. There are many range-based techniques available, like an approximate point in triangulation and lateration, multilateration, and the modified centroid method, which are categorized under static techniques.
- **Dynamic:** In the case of the dynamic method, continuous tracking of sensor nodes is required as they are moving and changing their coordinate values. A little extra time is required to find the positions of the moving nodes; for tracking the position of moving nodes, an accurate localization feature is required using this process. Track the location of moving target nodes it is very difficult because it has to be determined periodically. Road navigation in the absence of GPS features is a property of Kalman Filters [51-52]. In order to predict the system's future states, the Kalman filter is one the useful technique.

1.7 LOCALIZATION ISSUES

In many real-time applications, the localization concept is becoming an important and essential requirement in the field of WSN. Some of the concerns that need special attention are mentioned here.

- **Node Energy:** The sensor nodes have non-replaceable and limited-energy battery units for performing the operations, such as sensing and reporting. The whole system becomes worse if special care is not taken with regard to battery units [24]. Therefore, it is necessary to build an efficient algorithm that uses less energy.

- **Node Mobility:** Maintaining the node's connectivity in the mobility scenario is quite a challenging task in localization. In the case of static WSNs, the node, once estimated, is not going to change its position as it is fixed, but, in the case of dynamic WSNs, the nodes periodically shift from one position to another position, and the deployed sensor node has to determine and estimate the position periodically [53].
- **Transmission Range of a node:** In localization technique, a beacon signal is required for determining the locations of unknown nodes. Beacon nodes are equipped with a GPS feature which helps these nodes to be placed at a position with known coordinates, and, with this feature, one can obtain a proper connectivity in between the beacon and the target nodes. So, the transmission range of a node plays a key role in estimating the locations of unknown nodes.
- **Localization Accuracy:** To determine the accuracy the difference among actual and the estimated position of the sensor node is calculated. It is a quiet hard to obtain the accurate location of the sensor node by applying localization algorithms. So, by using available or new localization algorithms, it is possible to obtain optimum results [54-55].
- **Localization Security:** As in WSNs, most of the times this set-up is installed in unfriendly locations. Some of the problems that occur in localization are overshadowing and distance away from attack [56].
- **Deployment in 3 D:** Complexity in the 3D localization is very high. As in 2D there are so many localization schemes are available but in 3D very limited schemes are there.

1.8 MOTIVATION

The motive here is to design Meta-heuristic approaches for optimum localization of static and dynamic WSNs. In WSN, a large number of distributed devices equipped with sensors are deployed to monitor environmental phenomena. There are some challenges in WSNs that restrict achieving the accurate position of each node.

- **Node to Node accurate Measurement:** In localization, we measure distance between one node to other. For many applications node to node measurement accuracy should be high. So, accurate location of node is a big challenge in localization process.
- **Node Mobility:** Mobility support in WSN is very critical. However, it is an important research issue to know the existing solutions for mobility in WSNs and localize the target nodes in dynamic scenarios.
- **Scalability:** The algorithms used for localization are required to be suitable for sensor deployment in large scale networks with less anchor nodes also.
- **Power Management:** Numerous WSN applications need a longer network lifetime due to their surveillance nature. Thus, offering an area with an energy-efficient monitoring service is a crucial research problem. Likewise, localization algorithms necessitate energy-efficient computation.

While developing the localization algorithms, the above-mentioned parameters are required for WSN implementation in various applications. These challenges make the WSNs localization research unique and interesting even after a decade of intense research. Our basic focus in this work is to make the proposed localization process more accurate, cost-effective and computationally efficient in mobility-based scenarios. Taking into consideration of these factors, objectives have been proposed for this work in the following section.

1.9 OBJECTIVES

Based on the application requirements, in localization process, factors like accuracy, scalability, energy consumption and mobility should be considered. In this work, our major focus is on achieving high node location accuracy with very less number of anchor nodes in dynamic (Anchor and Target node may have some mobility) and static scenarios by using the applications of met heuristic based algorithms. The proposed objectives are:

1. **Designing a range based error control model for estimation of 2D and 3D optimal node location in homogeneous dynamic environment with various novel soft computing approaches.**
2. **Designing a range free error control model for estimation of 2D and 3D optimal node location in homogeneous dynamic environment with various novel soft computing approaches**
3. **To analyze and appraise a stochastic algorithm for homogeneous 2D and 3D range free dynamic WSNs which are able to calculate the optimized coordinates of target nodes.**
4. **Comparative analysis of existing techniques with the proposed techniques at different stages for validation of the proposed algorithm.**

1.10 CONTRIBUTION OF WORK

Our research work is focused on calculating the unknown locations of target nodes using a single anchor node. To achieve accurate, energy efficient and low cost localization, some efforts have been made to estimate the dynamic node location in 2D & 3D environments for range based and range-free approaches. In this work, mobility has been assigned to target nodes in some scenarios and in some scenarios, mobility has been given to the anchor node. To make the algorithm energy efficient and cost effective, only one anchor node has been utilized to estimate the target node position. Further, approaches like DA, NNA, APPA and TSNMRA have been utilized to get optimum results. The thesis makes the following significant contributions:

2D range-based Localization with target mobility: This contribution proposes the concept of introducing virtual anchors to locate mobile target nodes in a two-dimensional scenario by various meta-heuristics separately. The novel proposed algorithm Dragonfly-Firefly (DA) Metaheuristic, is implemented for 2D WSNs. To locate unknown nodes, only one anchor is used. A node whose position is known is normally deployed in the middle of the region which is to be sensed. To begin, the anchor and the target node distance is calculated after the notion of VN’s is proposed, with VN’s placed at certain angles in the field at a defined distance between the anchor and the target node. The centroid is calculated, and DA is used to compute the localization error. Similarly, one more approach has been proposed in a similar fashion and environment. Here, for computing the location of randomly moving target nodes, an algorithm is known as Neural Network Algorithm (NNA) is being proposed and used. The concept of NNA can also be utilized in 3D Localization to find the exact location of the nodes.

3D range-based Localization with target mobility*:* In this work, we demonstrate the application of novel 3D node localization algorithms based on various met heuristics to moving target nodes using one anchor node. In a simulation-based scenario, the middle and lower levels include nodes with uncertain positions, whereas the top layer has a single anchor node. Adaptive Plant Propagation Algorithm (APPA) is a revolutionary soft computing approach presented to determine the optimal placements of these mobile nodes. These nodes are diverse and have been deployed in an asymmetrical environment with a DOI value of 0.01. Simulation findings demonstrate that the proposed APPA method surpasses previous meta-heuristic optimization strategies in respect of localization error, computational time, and localization determination.

3D range free localization with target mobility: For Localization, a single movable anchor node is considered. In an anisotropic environment, target nodes and anchor nodes are distributed across the borders of three layers. Anchor nodes are placed in the top layer, while target nodes are scattered in the middle and bottom levels. A fuzzy Logic System (FLS) has been used for the modeling of RSS and edge weight to reduce computational complexity. Further, the Tunicate Swarm Naked Mole Rat Algorithm (TSNMRA) is used to optimize the membership function bases of RSS and edge weights in order to reduce the position error. Even though this mobility-based approach is presented for the first time, simulation results indicate that the proposed technique achieves greater localization precision than static range-free schemes.

1.11 THESIS ORGANIZATION

The organization of the thesis work has been represented chapter wise with the major points are being covered as:

In chapter 1, we first present the overview WSN, its architecture, features, applications, localization in WSN and the associated challenges. We also conduct the study of localization approaches covered by the range-based and range-free category against their merits and demerits and the various metrics used for the evaluation of the localization. The research motivation, research objectives to accomplish and contribution of the thesis have also been discussed in this chapter.

Chapter 2 provided the comprehensive literature work on range-free and range-free localization techniques for the static and dynamic scenarios; localization based on 2D and 3D environments and met heuristic approaches based on localization. Further, it also mentions the other related research work to reduce the error of the localization process. It also includes the research gaps, criteria for evaluation and parameter calculation to be done for the execution of the proposed research work.

Chapter 3 presents a novel hybrid DA optimization technique. Further, the implementation of above said algorithm is applied to a mobile 2D environment using a single anchor node. The effectiveness of the DA method is determined by getting results and comparing performance metrics such as the number of localized nodes, location, and scalability. Moreover, for computing the location of randomly moving target nodes, an algorithm known as the Neural Network (NN) algorithm is presented. A node whose position is known is normally deployed in the middle of the region which is to be sensed. Acquiring results and comparing performance parameters such as the number of localized nodes, location, and scalability is being used to measure the success of the NNA approach.

In chapter 4, the problem extension of 2D mobile target node localization into 3D localization problems using an anisotropic environment has been done. Here, the Adaptive Plant Propagation Algorithm (APPA) approach is being presented to determine the optimal placements of mobile nodes. Simulation findings demonstrate that the proposed APPA method outperforms previous meta-heuristic optimization strategies in terms of localization error, computational time, and the sensor nodes that are located.

Chapter 5 presents the range-free 3D localization technique named TSNMRA. Here, a single mobile anchor node is considered for localization. Target nodes and anchor nodes are deployed over three-layer boundaries in an anisotropic environment. Additionally, the weights of the edges among each target node and its neighbors are employed and these weights are represented using the Fuzzy Logic System (FLS). TSA and NMRA lower the localization error by optimizing their edge weights. The simulation result of the proposed algorithm gets better localization accuracy as compared with static range-free schemes.

Chapter 6 deals with the overall conclusion and future work of the work carried out in this thesis. This chapter summarizes the significant contributions and ends with some proposals to be covered in future.

1.12 SUMMARY

This chapter provides an introduction related to the fundamental concept of WSN, such as architecture, applications, features, localization in WSN, localization issues, and the process of localization. It also covers the major classification of localization algorithms along with their basic concepts. In the next chapter literature review associated with our research is presented along with the metrics for evaluation.

CHAPTER -2
LITERATURE REVIEW

In this chapter, the comprehensive literature work on range-free and range-free localization techniques for the static and dynamic scenarios, localization based on 2D and 3D environments and met heuristic approaches based on localization is described. In addition, this chapter also mentions the other related research work to reduce the error of the localization process. It also includes the research gaps, criteria for evaluation and parameter calculation to be done for the execution of the proposed research work.

2.1 TRADITIONAL LOCALIZATION ALGORITHMS RELATED WORK

WSNs nowadays are treated as an emerging technology, used for various applications like investigation of natural resources, tracking of static or dynamic targets, and in areas which it is not easy to access. A WSN consists of different types of sensors, which may be homogenous or heterogeneous [57]. The main challenges faced in WSNs, which degrade the performance, are computational, battery lifetime, security, and localization. The localization procedure is used to assign coordinates to unidentified nodes throughout the sensing area. Localization techniques can be used in WSNs for different applications, such as tracking of targets and location tracking of target nodes, etc. Many researchers have presented a variety of localization algorithms for improving important parameters, namely accuracy and efficiency. These approaches are categorized primarily as range-based or range-free localization strategies like (RSSI) [58-59], (TOA) [60-61], (TDOA) [62], (AOA) [63-64], are classified as range-based techniques. Using either angle information or distance, the range-based localization approaches determine the position of an unknown node. A huge deployment is involved in implementing this method, but these methods are more effective at localizing the node effectively and guaranteeing accurate node localization as compared with range-free techniques.

In WSN, deployment is not always static. It may also be dynamic, but there are a few problems that need to be overcome, like the maintenance of link, scope, and usage of energy. The present trend in today’s WSNs puts mobility in a positive light.

Localization is the main requirement as well as the biggest challenge for dynamic WSNs. The accurate positions of the nodes placed in the sensor field must be known in order to identify the most efficient route. The sensor nodes may also move from one point to another during their run-time in the case of dynamic WSNs, but the position of sensor nodes is not going to vary from its original position in the static scenario. Thus, locating unknown target nodes in dynamic environments is of prime concern.

In [65], the authors propose one new approach Convex Position Estimation (CPE), for enhancing localization accuracy. In this work, three anchors having a similar transmission range corresponding to an unknown node exists in the overlap region. CPE is a centralized algorithm and, because of its resource restriction feature, is not able to do the complex computation required for optimization. In [66], the authors develop a scheme for large-scale WSN named Approximation Point in Triangulation (APIT), in which a few numbers of devices are connected with GPS, and their number can be changed on the basis of network and node density. APIT approach separates the network in the form of a triangular area among the anchors. This APIT scheme works well when random node deployment and irregular radio-pattern are there and thus leads to less overhead. In [67], the authors suggest a hop-based position estimation algorithm that works on the concept of Distance Vector (DV). The advantage of this approach is its simplicity and independence from range measurement. The usefulness of the method is enhanced by its simplicity. The disadvantage is that it can only function in an isotropic system. In [68], the authors propose an approach named Weighted Centroid Localization (WCL). This approach is intended to overcome the less precise location estimation of the Centroid. They used the weight factor to improve the localization approach. Weight is the function that depends on the sensor node's distance and features. The pitfall is that the nodes that the anchor's immediate neighbor can be localized. The benefit of the WCL is its fast execution nature and simplicity for finding the location of the node.

In [69], the authors develop a new Hierarchical Multi-Dimensional Scaling (MDS) based localization approach. This author divides this approach into three steps. Here, the sensor node can work as cluster-head, cluster-member, and in the form of a gateway. In [70], the authors propose two algorithms and, after that, combine them into Self Adaptive Positioning (SAP) algorithm. In [71], the authors develop a new approach combining the centroid and DV-Hop. In this work, the pitfalls of the two localization scheme, which are centroid localization and DV-Hop, has been elaborated and proposed a new algorithm. This approach has not noticed any effect in the improvement of the localization accuracy, but this approach is less complex, and the localization error in this approach is less as collate to centroid localization and the DV-Hop. The work mentioned in [72] highlights an approach that is centralized in nature and location is calculated by the centric powerful Base Station (BS). It contains three steps in which, initially, sensors determine the pair-wise gap matrix. To get this gap matrix, the whole network is broadcasted with message packets. In order to get the matrix, there is a need for flooding of packets and that is the reason for more power consumption. After that, this gap matrix works as input for the Multi-Dimensional Scaling (MDS) method. This approach is effective and found to be accurate as compared to other approaches. It is easy to implement and, in computation, less complex. Hence, MDS is also used for distributed localization.

2.2 TARGET NODE LOCALIZATION RELATED WORK

As many advances and improvements in the field of wireless communication have taken place in recent years, this has encouraged the use of WSNs in many real-world applications. Localization of sensor nodes becomes necessary in almost every application in WSNs. There are a variety of localization techniques found in the literature for determining the position of an unknown node, which is feasible with or without anchor nodes.

2.2.1 2D Localization Related Work

In [14], authors have examined outdoor localization without using GPS features in their study. They calculated the coordinates of the unknown nodes using the centroid process. Lee et al. [73] used fewer anchors to demonstrate their work on localization. They achieved a high level of accuracy in estimating distance by finding shorter distances. In [74] authors proposed some methods for distance estimation: the first was to use available statistical techniques and then apply the neural network concepts to compute the distance. Their findings were focused on parameters that reduce the accuracy of distance measurements, such as transmitted power, Radio frequencies, node mobility, etc. In their paper, [75] two variants of bat optimization algorithm (BOA) are proposed to localize the sensor nodes in a more efficient way and to overcome the drawbacks of original BOA, i.e. being trapped in local optimum solution. The exploration and exploitation features of original BOA are modified in the proposed BOA variants 1 and 2 using improved global and local search strategies. To validate the efficiency of the proposed BOA variants 1 and 2, several simulations have been performed for various numbers of target nodes and anchor nodes, and the results are compared with original BOA. The positions of the nodes are computed using this geometric relationship. In [79], the authors presented MBAL (Mobile Beacon node localization problem. [76] This paper proposes an improved Savarese algorithm to the problem of singularity in WSN node localization. The proposed algorithm is a modified version of the conventional Savarese algorithm, and it solves the singularity problem and improved the positioning accuracy. Simulation results show that the proposed algorithm effectively improved system performance, and the accuracy is improved over 2.83% and 2.96% than the existing algorithms. The proposed scheme is effective for indoor environments while it can be deployed outdoor for small-scale.Sumathi and Srinivasan [77] employed a single anchor node and the least-squares method to identify the precise placements of static target nodes based on RSSI data.

In [78] authors used the PI method to present a different approach in which no such association or mapping -Assisted Localization), a method for range-dependent localization in which the mobility of the mobile anchor node is controlled by a strategy. Their plan provided the most route variety with the fewest complications. In [80], the authors explored range-free strategies which are energy oriented and use fewer anchor nodes in their conclusions. They believed that by using fewer anchor nodes, their technique is less complicated and more effective. In [81], the authors suggested a hybrid model termed as Lion Assisted Firefly Algorithm (LAFA) model has been introduced. In this conference, a parametric analysis is made on the proposed algorithm by varying the parameter in LAFA. This includes the performance analysis of the model under each variation. In [82], the authors developed an approach that belongs to the group of range-free techniques. Their research asserted that their approach is simple and practical, with comparisons between nodes based on RSSI values, which uses much less energy and demonstrates a high degree of precision by using movable anchor notions. In [83] authors suggested two algorithms for providing mobility in WSNs. Stone and Camp [84] addressed anchor-based localization algorithms and computed the efficiency and preciseness in relation to anchor mobile nature and target nodes. There is much more study that we have not described, and the results can be found in the literature [85–95].

In [96] authors used a Cosine Rule-based Localization (CRL) technique. Trilateration is used in existing techniques to find sensor node locations. In comparison to the present trilateration technique, simulation findings show that CRL gives more accurate results for all trajectories. In [97] authors stated that this study proposes virtual partition and distance correction (VP-DC) for minimizing error in the distance estimate step. The concept of a virtual partition algorithm is used to find each hop's distance on the least communication path among the beacon and the node which is to be traced. In [98] authors discussed that the purpose of this project is to develop a particle swarm optimization approach for localization that is based on velocity adaptation. The results show that the proposed method is more effective at improving location accuracy. In [99] authors describe a UNL (Unknown Node Localization) approach for a sensor position estimate. The suggested solution is based on RSSI and thus requires no additional hardware or data connection between sensor nodes. They conducted experiments to assess the correctness of the UNL approach in terms of localization, and they discovered that the proposed method is easy because it requires less computing and communication. For the correct estimation of unknown nodes, the suggested approach is compared to other current localization methods. The testing findings demonstrate the algorithm's usefulness and its capacity to more precisely locate unknown nodes in a network. In [100], the authors developed history-dependent multi-node cooperative localization, which is a distributed localization solution for sparse ad hoc wireless networks that measures the proportion of reference nodes (HMCL). In the suggested HMCL approach, they utilize a unique model to eliminate the incorrect estimate values based on prior positions of nodes.

2.2.2 3D Range Based Localization Related Work

In [101] authors have used UWB, a ToA technique, to calculate the requisite three-dimensional coordinates for a localization procedure. They explored how their technique is more accurate in comparison with other techniques. In [102], the authors proposed DV-Hop scheme that can more precisely and efficiently localize 3-D coordinates of a sensor node, but it's quite complex, and the deployment cost is very high. In [103] author presented a hybrid approach for optimization that merged DV hopping with the newton method. Also, for their proposed algorithm, the authors took into account major parameters: coverage and accuracy. On the basis of the RSSI model, Li et al. [104] created a model for finding 3-D positions in a WSN context. They suggested a model for determining the relationship between the DOI and variance in the transmitted signal's ranges. In [105] authors used a parametric approach to create an algorithm for determining 3-D coordinates. Due to the fact that the network is contracting towards a center element known as the central point, this method has fewer anchor nodes accessible for localization and may perform better. In [106], the authors suggested a localization approach that relies on a costly beacon signal. It has been inferred that MDS-MAP, DVHOP, and the Centroid approach are methods that have been updated from 2-D to 3-D coordinates and are available in the literature along with some applications in diverse areas [107–120]. Cheng et al. [121] and Zhou et al. [122] surveyed this technology when collecting 3-D coordinates in applications deployed in an underwater network. Localization is accomplished using knowledge dependent on connectivity and the number of anchors in these methods. In [123] authors defined a hybrid method for creating 3-D WSNs. This scheme employs an approximation based on the least-squares criterion [124-125].

By combining multi-group interaction and quantum feature methods having the Symbiotic Organisms Search (SOS) concept, S Chu et al. [126] created a novel global optimization technique named MQSOS. It is efficient and consistent, and it may be used for actual issues requiring several arguments. Comparing MQSOS against other intelligence algorithms under the CEC2013 large-scale optimization test suite by the authors. Experiment findings indicate that the MQSOS approach surpassed other smart methods. According to Kotwal et al. [127], distributed localization nodes evaluate their min and max distance limitations with regard to anchor nodes using crude RSSI. The approximation utilizes a basic binary search technique. The approximate distance limitations contribute to the formation of the node's feasibility region in connection to anchor nodes. In order to minimize localization error, the feasibility area locations are utilized as starting particles in PSO to resolve the optimization issue. Using basic calculations, it was revealed that nodes might be located with better precision than with present techniques, and a restricted range is required. In [128], the authors offer a localization solution for unidentified emitter nodes in a WSN. In this technique, it is assumed that there are four anchor nodes with known locations and single or more unknown nodes sending RF signals to be received by four anchor nodes. The primary data source for the system is an imprecise indication of signal strength. This work investigates the PSO technique, which may be applied in real-time to achieve a better approximation of the sensor nodes' positions. The modeling and experimental results of the proposed methodology are described. According to the authors in [129], the RSSI technique calculates the distance among benchmark and target nodes placed in the environment using the trilateration technique. In [77] authors presented an RSS technique for identifying unidentified nodes that requires just one anchor node. This research proposes a technique for identifying fixed target nodes using the approach of least squares. In [78] provided a mobile-oriented Perpendicular Intersection (PI) technique that explicitly does not map the RSS distances. Here the geometric PI relation is utilized to determine the node's placement. In [102] authors presented the DV-Hop dependent method for finding sensor nodes. This algorithm's downfall is mostly attributable to its complexity and increasing cost.

2.2.3 3D Range Free Localization Related Work

Numerous techniques are developed to cater to localization issues in WSNs. The connection information among an anchor node and a target node, as well as the amount of hop counts, play a significant part in range-free localization schemes in determining target node positions. Additionally, the basic centroid approach is used to obtain the locations of the target nodes. In [130], the author developed a range-free technique that depends on the proximity data utilized by a coarse-grained approach. In this technique, the centroid method is employed to determine the 2D positions of target nodes by taking into account the position of the anchor node [109]. Widespread in the existing work are methods to find the 2D coordinates of target nodes using range-free methods. Obtaining precise 3D positions of a target node, on the other hand, remains an outstanding research question. The primary contribution of research to 3D node localization utilizing range-free approaches is as follows: The authors of [131] devised a hybrid localization approach that calculates the 3D coordinates of a target node with greater precision by integrating RSSI and hop distance data. However, the strategy presented is not suitable for an uneven network. Moreover, two range-free localization schemes based on RSS data and using Computational Intelligence (CI) methods are shown in [132]. In the beginning, edge weights are modeled utilizing FLS and then optimized using the Genetic Algorithm (GA). In contrast, the second approach uses Neural Networks (NN) to determine the location by treating localization as a single issue. In their work [133], the authors developed a minimal localization technique using low-cost and small-area WSNs. This approach is entirely scattered and meets a strict authorization requirement for the sensor network in consideration. Authors in [134] proposed a method to enhance the Monte-Carlo approach by using an adjusted heredity computation based on the LMS values. The authors of [135] developed a flexible, iterative localization approach based on the steepest gradient descent. In [56], the authors developed a new technique that is a combination of the RSS and AoA methods, in which sensor nodes are randomly dispersed with unknown transmission power and route loss exponents. In [137] authors suggested two 3D-based range-free localization techniques using HPSO and BBO in the asymmetrical domain of WSN and argued that FLS might lessen the nonlinear relationship between RSS and distance. Two 3D techniques based on Bacterial Foraging Optimization (BFO) and Invasive Weed Optimization (IWO) are suggested in [73]. Reduction of computational cost and non-linearity among RSS and distance to improve localization precision by mapping edge weight among both the target node and its closest anchor node utilizing FLS has been executed here. A range-free approach for multi-hop propagation in an anisotropic network is addressed in [82]. The variation in hop count between the shortest route and direct path creates a detoured route among nodes. The route diversion is utilized to determine the new distance for the optimal path. In [137] authors provide a technique based on 3D DV-HOP localization using PSO. The proposed approach is more precise than the conventional DV-HOP method.

2.2.4 Optimization Related Work

The Authors presents a comparative analysis of the different test case optimization techniques. There are various optimization techniques available for the context. This review explains about the different optimization techniques on the basis of their evolution, methodology, performance and applications [191]. In this an attempt is made to review the literature on different modern optimisation techniques for cutting parameters in machining. The review is kept general in nature, without considering special cases like, multi-objective optimization problems, linear programming, multidisciplinary optimization problems, convex problems, etc. Although various optimization methods have been proposed in recent years, but some more popular optimization techniques such as Genetic Algorithm, Ant colony method, Honey Bee Algorithm, Simulated Annealing are presented here [192].

2.3 META HEURISTIC IN WSN LOCALIZATION

Computational Intelligence (CI) is the approach used to solve complicated problems that are inspired by nature. CI may be used efficiently in a variety of real-time situations. In contrast to Artificial Intelligence (AI), CI systems may make decisions on their own, i.e., a system can determine its optimal fitness or resolution by using a variety of methodologies [138]. Applications of CI are now used in several industries, including decision support, genetic clustering and classification, consumer electrical products, the equity markets, time-series prediction, medicine, and a variety of bioinformatics issues.

2.3.2 Genetic Algorithms in WSN Localization

This is a technique based on search and optimization and is used for finding the estimated results. It begins its search with random solutions, and these solutions are assigned a fitness function that is relative to their objective function. Then, a set of new populations is formed by using three genetic operators named reproduction, cross-over, and mutation. An iterative operation in GA takes place using all three operators until a terminated criterion is not reached. For decades, GA has been used in a wide variety of applications because of its simplicity. The working of the same has been defined in figure 2.1.

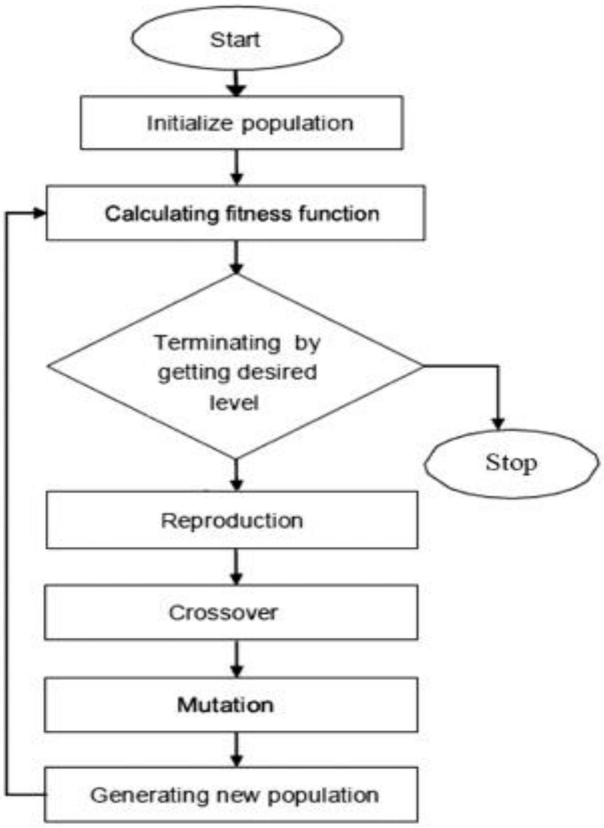


Figure 2.1: Working layout of GA

In [139], the authors have suggested a technique that modifies the hop count by changing a correction factor and then optimizes the updated hop size using a line search algorithm. The idea of co-planarity is developed in order to eliminate location inaccuracies induced by coplanar nodes. The precision of localization is further enhanced by using a GA. Later on, in [140], authors developed Salp Swarm Algorithm (SAA), a contemporary bio-inspired algorithm. The suggested approach contrasts with the good optimization techniques, including PSO, BOA, FA, and GWO for various WSN operations. On a similar note, in [141], authors have suggested a technique that uses the Fruit fly Optimization Algorithm (FOA) to minimize the difference between the predicted and actual sensor positions. In the proposed scheme, a group of flies is initialized in the search region with random values for direction and distance. Using fitness, researchers then identify the flies with the greatest odor value to estimate the position of the destination point. A similar kind of work has been done by other researchers using the essence of GA during the localization process [142-147].

2.3.3 PSO Related Work

Kennedy and Eberhart created PSO [148], which is dependent on bird behaviour. It is an effective strategy whose execution phase is simpler. A random number of particles are distributed across space. The movement is then applied to the deployed particles in the search area. A moving particle in the search space gathers the 'pbest' and 'gbest' locations. The working of the same has been defined in figure 2.2.

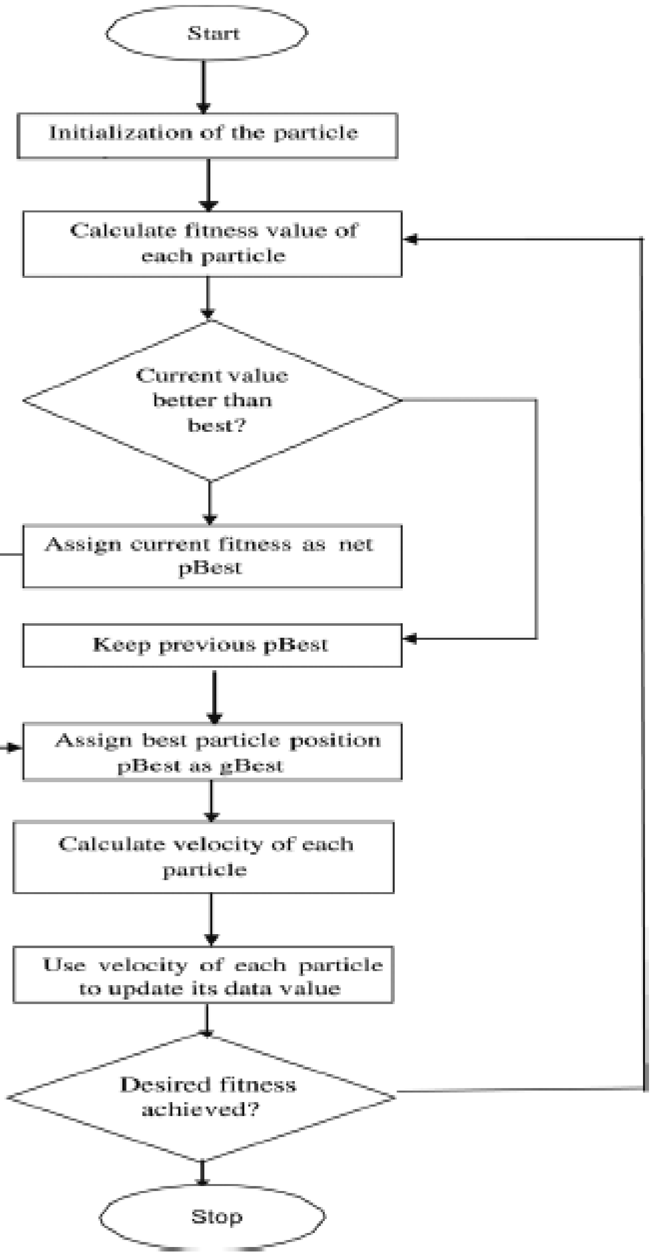


Figure 2.2: Working layout of PSO

In [149], the authors have developed a 3D approach based on PSO. First, they describe an enhanced technique (MDV-Hop) in which the average distance for every hop of anchor nodes is computed using RMSE and dynamically adjusted in groups with the weight RMSE associated with group hops. For more precision, they extended the adaptive optimization method PSO to the MDV-Hop localization technique and named as PMDV-hop. Authors in [150] utilize PSO for locating a source in complicated urban settings. PSO is executed so that each particle is represented by an Unmanned Aerial Vehicle (UAV) that directly measures and locates the global maximum of the carried out field. PSO is modified in a number of ways so that it might function well in this application. In [151], authors have suggested a novel localization paradigm for dispersed sensor nodes. The suggested system takes into account DV-Hop localization techniques using PSO. In addition, the radio irregularity model is addressed to demonstrate the applicability of the proposed approach in an anisotropic network. Some other related in this context have been highlighted and performed by the authors [152-157].

2.3.4 **BBO Related Work**

In BBO [158], the term HIS (Habitat Suitability Index) represents the fitness function. The higher the value of HIS, the better is the place for better survival of spieces, whereas lower HIS values indicate an inappropriate place for the species to live. The working of the same has been defined in figure 2.3.

In [159], authors have pointed out that increasing communication range and saving energy are major issues in WSN. To locate sensors in the area of interest, a BBO meta-heuristic approach is applied. The suggested method resolves a multi-objective issue using the traditional weighted sum technique. A fitness function is produced from a mix of competing goals, minimal interference, choosing the smallest number of sensors, and the network's connection limitation. The system determines the lowest number of sensors to place in the area of interest in order to optimize target coverage while reducing sensor interference. The suggested method is evaluated using both randomized and grid distribution. Some related work pertaining to the utilization of BBO has been expressed in the form of surveys and other research that has been done [160-164].

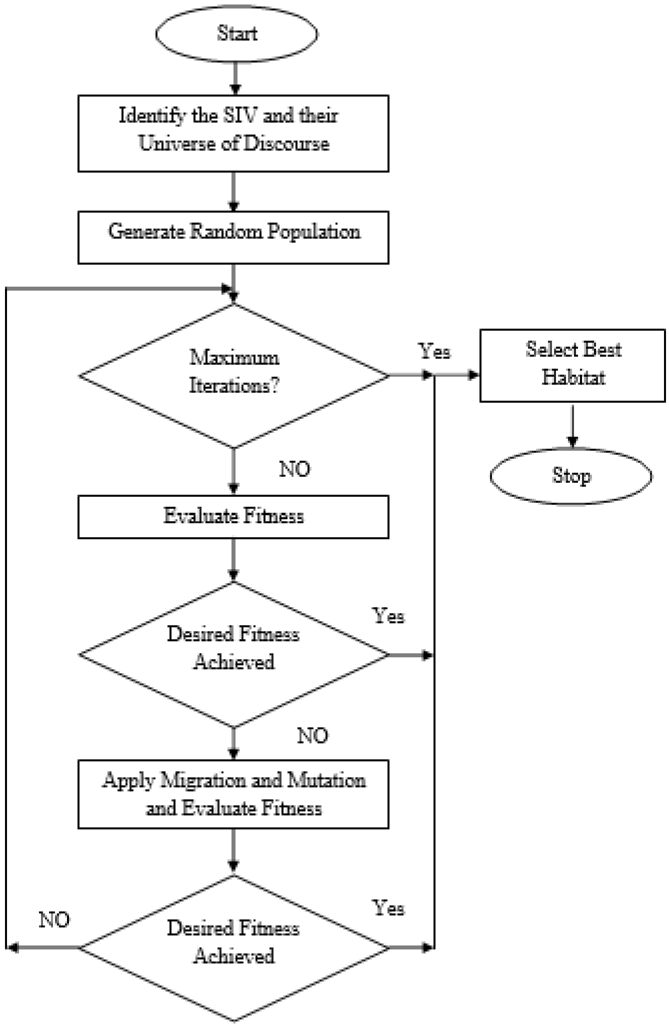


Figure 2.3: Working layout of BBO

2.3.5 FA Related Work

This algorithm was proposed by Yang [165]. The behavior of fireflies is used in this algorithm, and the rules followed by the fireflies are as follows: All fireflies are unisex as they move from one place to another, notwithstanding sex [166]. The parameter which attracts the fireflies towards each other is attractiveness, which is directly proportional to the glowing nature of the fireflies, and, as they move a certain distance apart, their brightness is reduced. So, fireflies will not follow each other in that particular case. If there is no brighter firefly found, then this event is random in nature. The fitness function, in this case, is represented by the glowing nature of fireflies. According to the Free Lunch theory, no single algorithm is best-suited to each optimization problem. There are many more types of optimization algorithms that are reported in the literature, which can be applied to localization problems to check their performance. The working of the same has been defined in figure 2.4

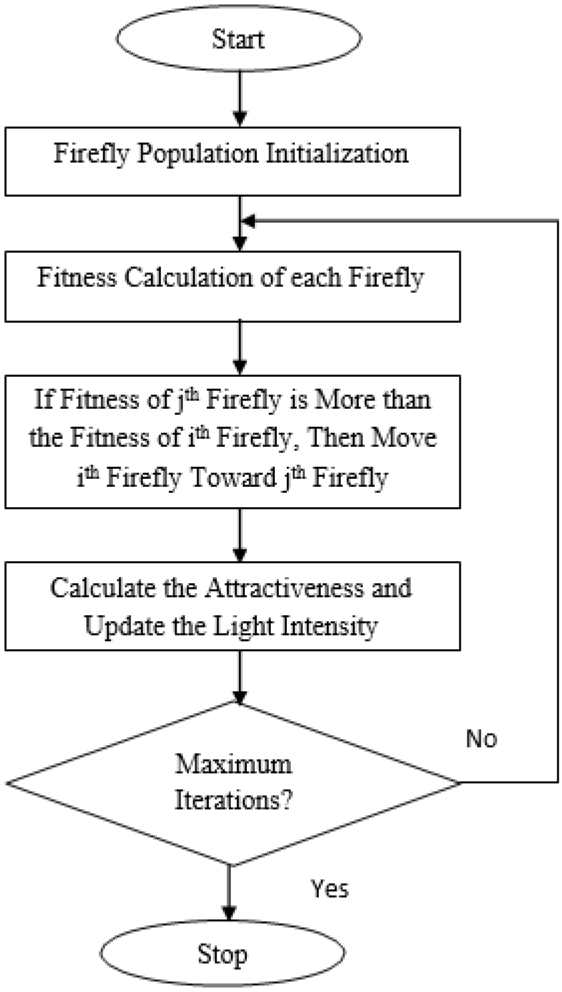


Figure 2.4: Working layout of FA

Some work in the direction of FA and Dragonfly Algorithm (DA) utilization has been expressed. In [167] authors have provided a detailed survey that covers the thorough analysis of the so-called DA and have highlighted its key aspects. DA is regarded as one of the most promising swarm optimization algorithms due to its successful application to a wide variety of optimization problems in a variety of fields. The review outlines the research on DA, including its forms such as linear, discontinuous, alter, and hybridization. In [168], the authors have suggested a revised version of the DA, which is afterward used to increase the lifespan of WSNs. The performance of the suggested augmented DA Metaheuristics is evaluated by comparing it to its original conception, the classic LEACH method, and the PSO. Some other prominent work has been done by the other researchers in the same context has been mentioned in the literature [169-173].

2.4 OPTIMIZED LOCALIZATION RELATED WORK

In [174], authors have introduced a novel Swarm Intelligence (SI) technique for identifying static nodes that have been computationally intensive, simple to execute, and need minimal memory. In [175], the authors employ the RSS range method and a PSO-based algorithm to effectively find sensor nodes. Localization-wise, the strategy has a greater success rate. In [176], the authors created the PSO-Iterative distributed iterative localization technique. Each target node has more than three anchors, and PSO is utilized to decrease the localization error. In [54], the authors suggested localization solutions depend on HPSO and BBO concepts with minimum hardware requirements, called, respectively, Range free HPSO and BBO. Their weights of the edges are optimized utilizing PSO and BBO algorithms. Arora and Singh [177] recommended using the BOA optimization method to optimize the location of unknown sensor nodes. BOA's performance in 2D settings is compared with the results of PSO and FA. In respect of convergence time and positional precision, their method surpasses existing meta-heuristic algorithms. Range-based approaches are extensively used owing to their increased accuracy; however, flip uncertainty is a significant drawback. The authors of [54-55] suggested a PSO-based AI system for detecting the location of moving nodes. The algorithm is separated into two steps, with anchor nodes positioned at the sensing area's edges. Using RSSI, distance computations were performed in the first phase. It was expected that virtual anchor nodes might find unknown nodes with the assistance of anchor nodes at a later time. In these phases, centroid calculations are performed in conjunction with the PSO optimization method, and the results infer a quicker convergence time.

In [178], the authors adopt the fundamental BAT method for the localization of nodes in WSN. To improve this, two BAT settings have been adjusted. The authors alter the basic BAT by using BFO. The authors of [179] suggest a method based on Grey Wolf Optimization (GWO). This author incorporated the GWO method to address the localization issue. The grey wolf density and coefficient vectors had first been generated via the GWO method. GWO is superior due to its hierarchical leadership structure. The authors of [180] present a novel technique for node localization based on an efficient Bat algorithm. The efficiency of this strategy relies on the adaptation of bat speed by fusing it with the impact of doppler in order to enhance performance. In [181], the authors offer a novel technique for WSN node localization based on DV-Hop and Modified PSO (MPSO). Late-evolutionary inaccuracy and a slow convergence rate are the drawbacks of the PSO.

The authors currently rely primarily on the optimization process to enhance the accuracy of localization. Previously, we explored a number of localization algorithms that use a variety of optimization techniques to enhance localization. After examining these methods, we've determined that there are only a handful of algorithms capable of high precision, low cost and optimization of the process. In WSN, therefore, a robust localization method is required.

2.5 RESEARCH GAPS

Following gaps has been observed during literature survey are mentioned below.

1. Localization of nodes in WSN is of utmost importance since event detection is impossible without precise location information. Therefore, localization is an essential aspect of WSN.
2. In WSN, the distributed and centralized nature of localization has a significant effect. Because of single point failure, decentralized localization in WSN is preferable to centralized localization. However, the construction of distributed methods is a hard task.

3. In most of the papers, minimum 3-4 anchor nodes are required to obtain locations in 2D or 3D environment. So, there is a requirement to find target nodes in 2D or 3D WSN by deploying fewer anchor nodes. This will reduce the deployment cost, which is one of the basic requirements in WSNs.

4. In range-based algorithms the level of accuracy achieved is upto 90%. So, there is a scope of improvement as accuracy is not achieved to the optimum level.
5. The convergence time of optimization algorithm can be reduced to locate target nodes quickly in 2D-3D WSN.

2.6 PARAMETERS AND CRITERIA FOR EVALUATION

In WSNs, multiple errors occur, such as errors due to range problems, errors due to non-availability of GPS signals, and sometimes localization algorithms, which are used for certain applications, degrade the accuracy of the system. Range error arises due to incorrect measurements carried out on the basis of distances. Similarly, errors in anchor position lead to a GPS error. There are certain parameters on which the algorithm's performance depends, such as accuracy in terms of location, cost and coverage. The evaluation procedure is described in Fig. 2.5.

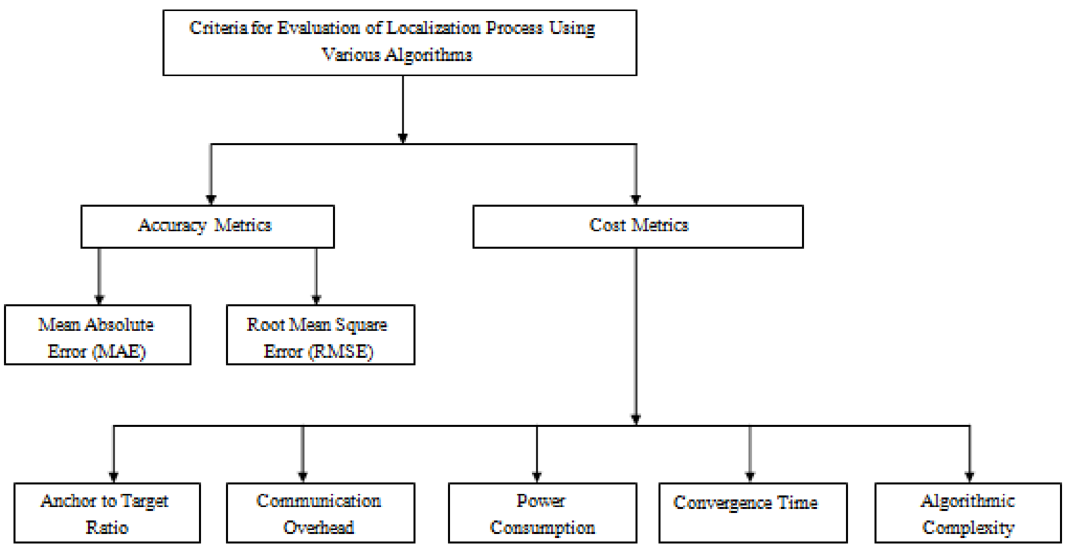


Figure 2.5: Taxonomy of parameters for localization evaluation

- **Accuracy in Location**: In this, the difference between the node's original position and the estimated position is calculated using any localization algorithm and the difference between the two leads to an error. By using this information, the determination of the accuracy parameter is calculated; the smaller the error, the greater will be the accuracy, and vice versa.

- **Flexibility to Error and Noise:** The localization algorithm chosen for the determination of location should be flexible enough to combat errors or noises originating from the input side.
- **Coverage**: The coverage parameter depends upon a few conditions, that how many anchor nodes are to be deployed in the sensor field. The larger the number, the better the coverage.
- **Cost:** In this, the cost parameter is evaluated on the basis of power consumed and the time taken by the algorithms to localize the nodes, so that communication between the nodes can be initiated.

2.6.2 Metrics for Accuracy

The accuracy term is used to match the positions of the actual and the estimated target nodes. The difference between the two positions leads to errors and these errors are named the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE).

- **MAE:** It is calculated in case of continuous variables and it is used to find out the accuracy of localization algorithm in a specified application. The equation of MAE in Eq. (2.1), where, (x_t, y_t, z_t) is current position and (x_e, y_e, z_e) is calculated position. N: represents total count of sensor nodes deployed.

$$Absolute\ Error = \frac{\sum_{t=1}^{Ni} \sqrt{(x_t - x_e)^2 + (y_t - y_e)^2 + (z_t - z_e)^2}}{N_t} \tag{2.1}$$

- **RMSE:** The parameter is also representing the measure of accuracy and is given by the Eq. (2.2).

$$RMSE = \sqrt{\frac{\sum_{t=1}^{Ni} (x_t - x_e)^2 + (y_t - y_e)^2 + (z_t - z_e)^2}{N_t}} \tag{2.2}$$

In almost every application, cost factor determination is an important parameter. In the localization process, the parameters which contribute in terms of cost are power consumed during the set-up stage, anchor nodes required during this process, and the total time required to localize all the unknown nodes. As an enhancement of the network in terms of life span is important, but at the same time, cost management also plays an equal role. There is a trade-off between these two. The ratio of known positions of the anchor nodes to the unknown positions, power consumed, and total time a localization algorithm requires localizing all the nodes play important roles in determining cost metrics.

- **Anchor to Target Ratio:** In terms of cost metrics, anchor nodes are the ones which are deployed in the sensing field with GPS features enabled in them. In order to save the cost, we need to install only a few anchor nodes in the field as they are expensive, and, are used to locate all unknown nodes.
- **Overhead during Communication:** As number of sensor nodes in any region of interest increases, the communication overhead also increases to a greater extent. The overhead is calculated by finding out the total number of packets sent.
- **Convergence Time:** The time taken by the localization algorithm to collect all the information regarding localizing all the nodes present in the network represents the convergence time. As the network size increases, this parameter is affected.
- **Algorithmic Complexity:** Algorithmic complexity is always defined with some standard notions (O), where the higher the order, like $O(n^3)$ and $O(n^2)$, the longer time it will take to converge, with this parameter representing the complexity.
- **Power Consumed:** This parameter is important in terms of cost as it calculates the power consumed in a localization process.

2.7 CONCLUSION

In this chapter, we reviewed the literature on range-free and range-based localization algorithms and schemes, as well as their functioning, environment, 3D implementation, and optimization. This chapter discusses the two major circumstances, the static and dynamic problems of WSNs. The literature on WSN localization describes in-depth the numerous obstacles in identifying the sensor node, which has been reviewed in this chapter. One of the most difficult tasks is locating the target node in a multidimensional plane. Many optimization strategies have been used in order to determine the precise placements of these sensors. There are also unresolved problems in this study field, such as localization in mobility-based situations and the use of fewer anchor nodes to save costs. As a result, numerous optimization strategies may be used to address the many challenges that arise throughout the localization process. There has been a lot of work described in the literature based on Metaheuristics for accurate localization. This chapter has shown some of these nature-inspired approaches and their application in different WSN scenarios. Furthermore, the parameters that are relevant for evaluating the algorithms are emphasized.

CHAPTER -3

LOCALIZING MOBILE NODES IN RANGE BASED 2D HOMOGENEOUS WSN USING DRANGONFLY AND NEURAL NETWORK ALGORITHM

To locate the node, the utmost parameter is to determine the coordinates of the nodes; otherwise, all the information which is accumulated using the other sensor nodes will be of no use, and hence the communication will be erroneous and may become a source of interference for all the nodes. Therefore, for the majority of applications inside WSNs, it is necessary to determine the precise geographical position of the target nodes. The Dragon Fly Met-heuristic method is suggested and presented in this chapter to calculate the position of randomly moving target nodes. A node whose position is known is normally deployed in the middle of the region which is to be sensed. The effectiveness of the DA method may be determined by getting results and comparing performance metrics such as the number of localized nodes, location, and scalability. Also, an algorithm known as Neural Network (NN) algorithm has been proposed for computing the location of randomly moving target nodes. A node whose position is known is normally deployed in the middle of the region which is to be sensed. Acquiring results and comparing performance parameters such as the number of localized nodes, location, and scalability can be used to measure the success of the NNA approach.

3.1 INTRODUCTION

In WSNs, to determine the physical behavior of sensor nodes, sensors are deployed in the natural environment. The sensor nodes deployed are cost effective and have less computational capabilities [182]. Some of the applications of WSNs are physical phenomena like monitoring the temperature, monitoring the habitat, and surveillance. WSNs also have various research challenges such as hardware and OS, installation, accurate location determination, QoS, network security, and so on. It is very important to find the accurate position or location of sensor nodes in WSNs. The simplest way to locate every deployed sensor node is to take the help of the GPS feature, although it is very costly when many nodes are deployed in the network. Various optimization algorithms are available in the literature that are cost effective and perform accurate location determination, but most of these algorithms do not suit well for a wide range of WSN applications. Range-based and Range-free localization are the two strategies available that are used to identify sensor nodes. The unknown nodes are determined using previous information of other nodes referred to as target nodes, and the known location nodes are anchor nodes. The coordinate's determination of target nodes can be calculated using the anchor's beacon messages, but it needs more power and high communication costs. If an algorithm estimates the wrong location, this error is distributed over the entire network. The accuracy of localization must be high. A number of high-accuracy meta-heuristic algorithms are documented in the literature.

In this work, one GPS-equipped node (anchor) is placed just at the center of the area, which is to be sensed, and all other unknown nodes are placed randomly and are allowed to move in the field. Whenever the target node drops within a known location of the anchor node, the measurement of the distance between the anchor and the target node is executed using RSS measurements. Then by projecting two virtual anchors within the network to locate target nodes (as at least for determining 2D coordinates, three nodes are required). The estimated node location is calculated by determining the centroid positions using these three nodes, and then the optimum location is calculated using the Dragonfly and NN algorithm as defined in this chapter and their comparison with the existing approach [183].

3.2 NODE LOCALIZATION USING DA

The suggested algorithm is imposed on the distinctive, superior swarming approach of the Dragonfly [166]. The dragonfly swarms for hunting and migration. The action of the hunting swarm is static and functions by forming a tiny unit of dragonflies that suddenly shift and change their moves. The maximum dragonfly flight over long distances in one direction characterizes the migratory behavior of swarms known as dynamic swarms. Static swarming and dynamic swarms show the ability of DA to manipulate and explore. The conduct of Dragonfly operates on the principle of harmony, a distraction from the opponent, isolation, alignment, and attraction to food.

Parting, organization, attraction, location, and diversion towards food adversary sources are all factors that influence dragonfly swarm migration. The static avoidance of collisions between persons and other individuals in the vicinity is referred to as separation (*Si*). Alignment (*Ai*) is the rate at which individuals match the speed of others in their vicinity. Individuals' proclivity to congregate at the neighborhood's mass core is referred to as cohesion (*Ci*). Each operator has been proposed with Weights, which are adjusted to ensure that the dragonflies arrive at the best answer. As the optimization process advances, the dragonfly's adjacent radius grows as well. The following can be discussed in terms of DA's mathematical implementation. Let *N* be the number of dragonflies. The location of the *ith* dragonfly is determined with Equation (3.1).

$$X_i = \left(x_i^1, x_i^2, \dots, x_i^d, \dots, x_i^N\right) \tag{3.1}$$

Herei=1,2,3,...,N, x_i^d represents the dragonfly's search space position, and *N* signifies the number of the search element. The fitness value is calculated using values which were generated between finite limits of variables. The weights are randomly initialised for each dragonfly for Si, Ai, Ci, food (f), and enemy (e) elements. Cohesion and Alignment coefficients are derived with Equations (3.2) to (3.4) for the updating of the separation of dragonflies as pointed below.

$$S_i = -\sum_{j=1}^{N} X - X_i \tag{3.2}$$

$$A_i = \frac{\sum_{j=1}^{N} V_i}{N} \tag{3.3}$$

$$C_i = \frac{\sum_{j=1}^{N} X_i}{N} - X \tag{3.4}$$

Wher V_i represents an individual's $i^{th's}$ speed and X_i depicts position. Current people situation is denoted by X, while the quantity of adjacent individuals is denoted by *N*. Food source attraction F_i is determined by Equation (3.5) and enemy diversion by Equation(3.6).

$$F_i = X^+ - X \tag{3.5}$$

$$E_i = X^- + X \tag{3.6}$$

Here X corresponds to current individual's location and food source is indicated by X^+ and X^- represents enemy source. Neighbourhood distance is determined by selecting *N*. Distance calculation, r_{ij}. It is determined by Equation (3.7).

$$r_{ij} = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{3.7}$$

If any dragonfly is found in the vicinity then the velocity is updated by Equation (3.8) and position by Equation (3.9).

$$\Delta X_{t+1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + w\Delta X_t \tag{3.8}$$

$$X_{t+1} = X_t + \Delta X_{t+1} \tag{3.9}$$

If in the neighbourhood radius there exist no dragonflies, then the dragonfly's position is found out by the Levy Flight equation, mentioned in Equation (3.10), as it improves the dragon flies random approach and enhances search capability.

$$X_{t+1} = X_t + Levy(d)X_t \tag{3.10}$$

Fitness function is evaluated on dragonflies' modified factors (Velocity, position). Position updating continues until the termination gets completed.

The procedure to find target nodes is:

a) One AN with number of TN's placed in 15x15 m^2 area.

b) When mobile nodes (target) falls in the vicinity AN, each TN keeps table of the distance among the two, as well as two virtual AN's in the area (because at least 3 nodes are mandatory for locating TN's). Figure 3.5 demonstrates idea of AN, VN and TN.

c) DA method is used to trace TN's location.

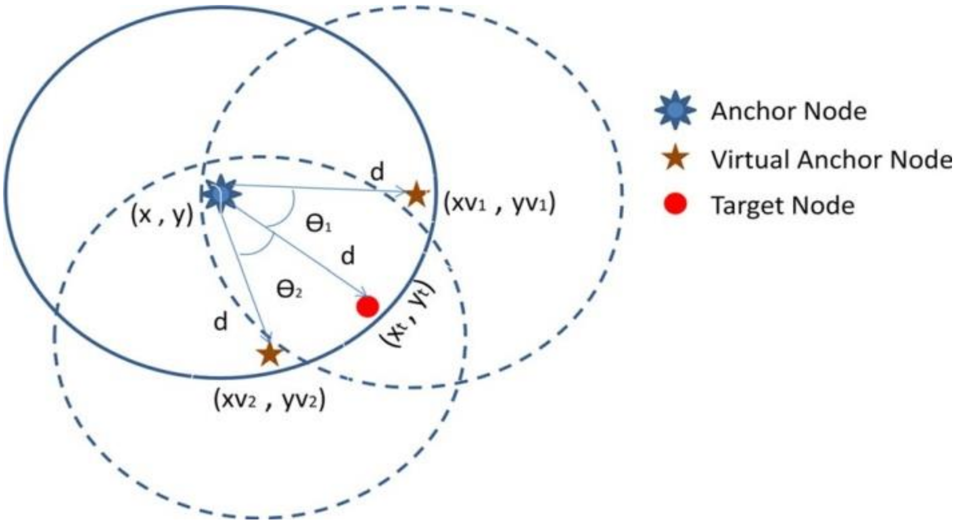


Figure 3.1: Sensor field schematic representation

As represented in Figure 3.1 where each mobile TN and AN is shown through Equation (3.11).

$$d_i = \sqrt{(x_t - x)^2 + (y_t - y)^2} \quad (3.11)$$

where (x_t, y_t) are TN positions, (x, y) is present AN's location. Centroid (x_c, y_c) is found out in Equation (3.12) and is shown in Figure 3.2.

$$x_c, y_c = \left(\frac{x + xv_1 + xv_2}{3}, \frac{y + yv_1 + yv_2}{3}\right) \quad (3.12)$$

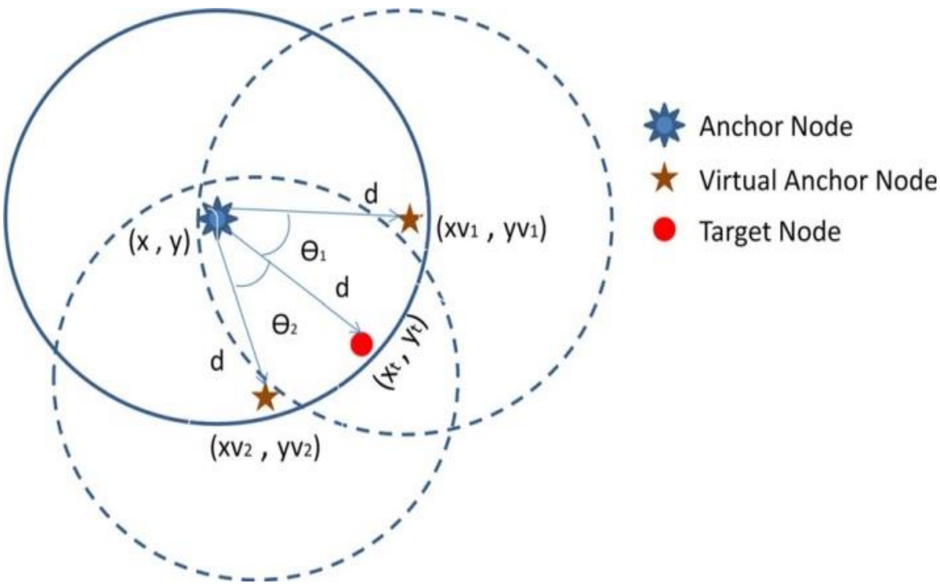


Figure 3.2: Computation of Centroid ANs and VNs

DA is used in Figure 3.3 to identify TN's coordinates, which is acknowledged by (x_s, y_s). Idea is the reduction of estimated and actual distance among the actual node and computed coordinates, which is expressed in Equation (3.13).

$$f(x_s, y_s) = \frac{1}{M}\Sigma\left(\sqrt{(x_e - x_i)^2 + (y_e - y_i)^2} - \hat{d_i}\right)^2 \quad (3.13)$$

Here, (x_e, y_e) depicts estimated position of target node, (x_i, y_i) depicts beacon node's *i* location which is placed at adjacent positions of target node and all count of beacons are depicted by M (M>3 here).

Localization error is found out by Equation (3.14) and is shown in Figure 3.4.

$$E_t = \frac{1}{N_L}\Sigma\sqrt{(x_e - x_t)^2 + (y_e - y_t)^2} \quad (3.14)$$

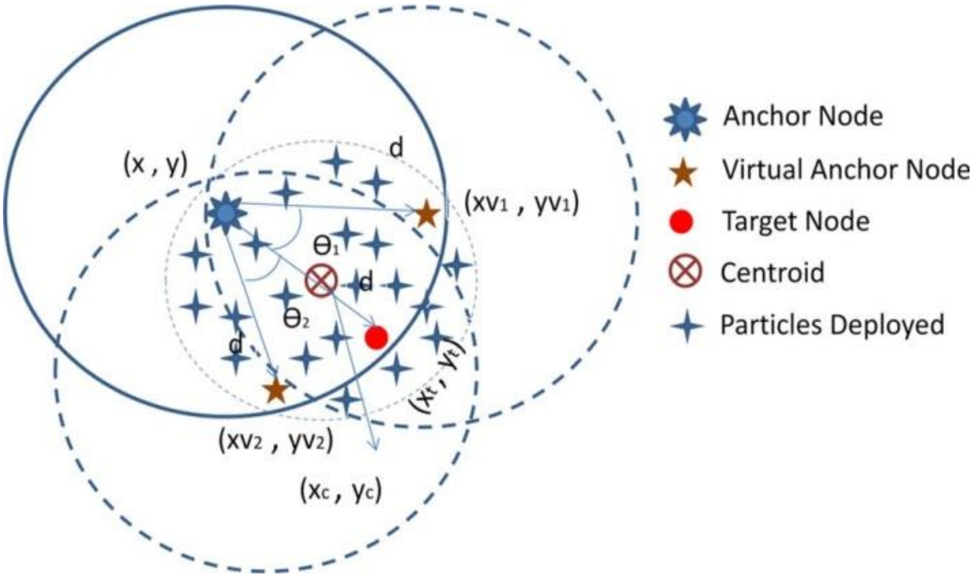


Figure 3.3: DA implementation around centroid

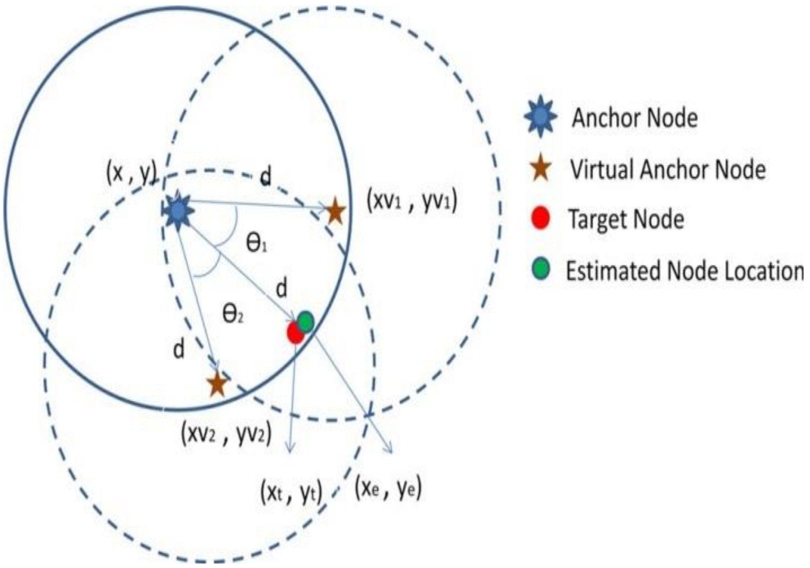


Figure 3.4: Estimated error using DA

For DA, the optimum target node placement is evolved until the termination requirements are met (or the minimum value E_t is reached).

3.3 RESULTS AND EVALUATION FOR DA

The proposed algorithm's performance is assessed using Matlab. The simulations have been run on a Windows with Intel i3, 8GB RAM. Simulations were carried out on a 15x15 m network. The anchor node is located in the sensing field's center (7.6 x 7.6 m), and twenty target nodes have been scattered over the sensing area. Coordinates of the AN and VN are shown in Table 3.1.

The specifications are: *AN-Anchor Node, TN- Target Node and VN-Virtual Anchor Node*

Table 3.1: AN and VN positions for DA

Coordinates	AN	VN1	VN2	VN3	VN4	VN5	VN6
X	7.6	10.116	5.248	2.508	4.497	9.315	12.399
Y	7.6	11.845	11.877	7.898	3.502	2.903	6.598

Table 3.2 represents that 20 TNs with a single anchor node and six VN are deployed in the sensing field.

Table 3.2: Distance between target and anchors for DA

S.No	Anchor	VN-1	VN -2	VN -3	VN -4	VN -5	VN -6
T N-1	4.82950833	7.98531255	9.66632634	8.83276928	6.12755065	1.66671265	3.43654076
TN-2	4.26851103	4.37430216	7.7494740	9.14328368	8.29970901	5.3981682202	1.401260626
TN-3	8.5018735	8.310563987	3.77985402	6.20284637	10.9015635	13.40183502	12.69929545
TN-4	2.89929145	6.39511197	7.90214601	7.50207102	5.29913699	2.499995240	3.201617112
TN-5	8.39870699	4.10205499	8.88174101	12.501056	13.2992601	11.16818198	6.501737897
TN-6	4.89950201	3.19893201	1.80172399	6.29958699	9.19875299	9.798026899	7.899525901
TN-7	4.69968299	7.40224402	9.60293911	9.3010610	6.59956802	2.402491899	2.610117902
TN-8	4.31039410	0.8665498	4.40288899	7.80207910	9.3026485	8.401907298	5.390450502
TN-9	8.70112402	13.5012802	11.1022899	6.40249901	3.91040102	8.410424702	12.40132899
TN-10	6.40145110	7.40278899	10.5998399	11.3015798	9.10289102	4.597013899	1.699306699
TN-11	6.79947601	6.10260610	10.2016699	11.7965732	10.6105502	6.802576201	2.102561291
TN-12	5.20183835	4.30287799	0.80118799	5.59803802	9.10242342	10.20516246	8.802607601
TN-13	7.39934864	12.4018636	10.5025068	6.25210532	2.39929863	6.730503386	10.80298624
TN-14	7.7020363	12.7100853	11.1020565	6.90161960	2.70306832	6.40204576	10.80223752
TN-15	4.80249901	4.20181902	7.89983201	9.80208599	9.10154640	6.101281902	1.601691482

TN-16	4.70201799	7.60110670	9.60124094	9.10205693	6.40151184	2.019539835	2.985462578
TN-17	8.09929335	4.89972836	9.69999799	12.6995792	12.7014989	9.702289775	4.80281335
TN-18	3.29929635	3.201947790	2.20172140	5.40198056	7.69996871	8.301812588	6.801570825
TN-19	8.19857681	12.956322	9.89945264	5.10208589	4.10287231	8.89919201	12.50233791
TN-20	5.39902139	8.71380340	4.81765821	0.6339412	5.29406879	9.137390165	10.39628467

Table 3.3 presents various optimization techniques used to localize the moving target nodes in the sensing field for five movements within a range of 10 meters corresponding to average localization error.

Table 3.3: Comparison of algorithms to compute localization error for DA

Algorithms	Movements	Transmission Range	Maximum Localization error(m)	Minimum Localization Error(m)	Average Error(m)
PSO	1	10	1.8674	0.1431	0.6944
	2	10	3.8233	0.2142	1.1234
	3	10	2.6978	0.1241	0.8132
	4	10	1.8914	0.2132	0.5878
	5	10	1.7897	0.1698	0.7432
HPSO	1	10	0.6827	0.1188	0.2445
	2	10	0.7623	0.0963	0.3532
	3	10	0.7336	0.0481	0.3334
	4	10	0.6591	0.2189	0.3487
	5	10	0.5271	0.2187	0.2205
BBO	1	10	1.4713	0.0321	0.3834

	2	10	1.4797	0.0779	0.8223
	3	10	1.4714	0.0363	0.6922
	4	10	1.4854	0.0442	0.7980
	5	10	1.6714	0.0582	0.9313
FA	1	10	4.6765	0.3834	2.3590
	2	10	5.8855	0.5865	3.0534
	3	10	4.8872	0.0323	2.4408
	4	10	5.2234	0.2454	3.1356
	5	10	4.6678	0.1980	2.5820
DA(Proposed)	1	10	0.6827	0.1188	0.2145
	2	10	0.7423	0.0893	0.3132
	3	10	0.7236	0.0281	0.3034
	4	10	0.6491	0.1989	0.2387
	5	10	0.5031	0.1878	0.2005

The localization error for DA is quite low as clear from figure 3.5 and also as inferred from Table 3.3, which comprises its comparison with other approaches. Here, the node location is calculated in DA with minimum localization error and shortest processing time. This is due to the exploration ability of the Dragon Fly Algorithm

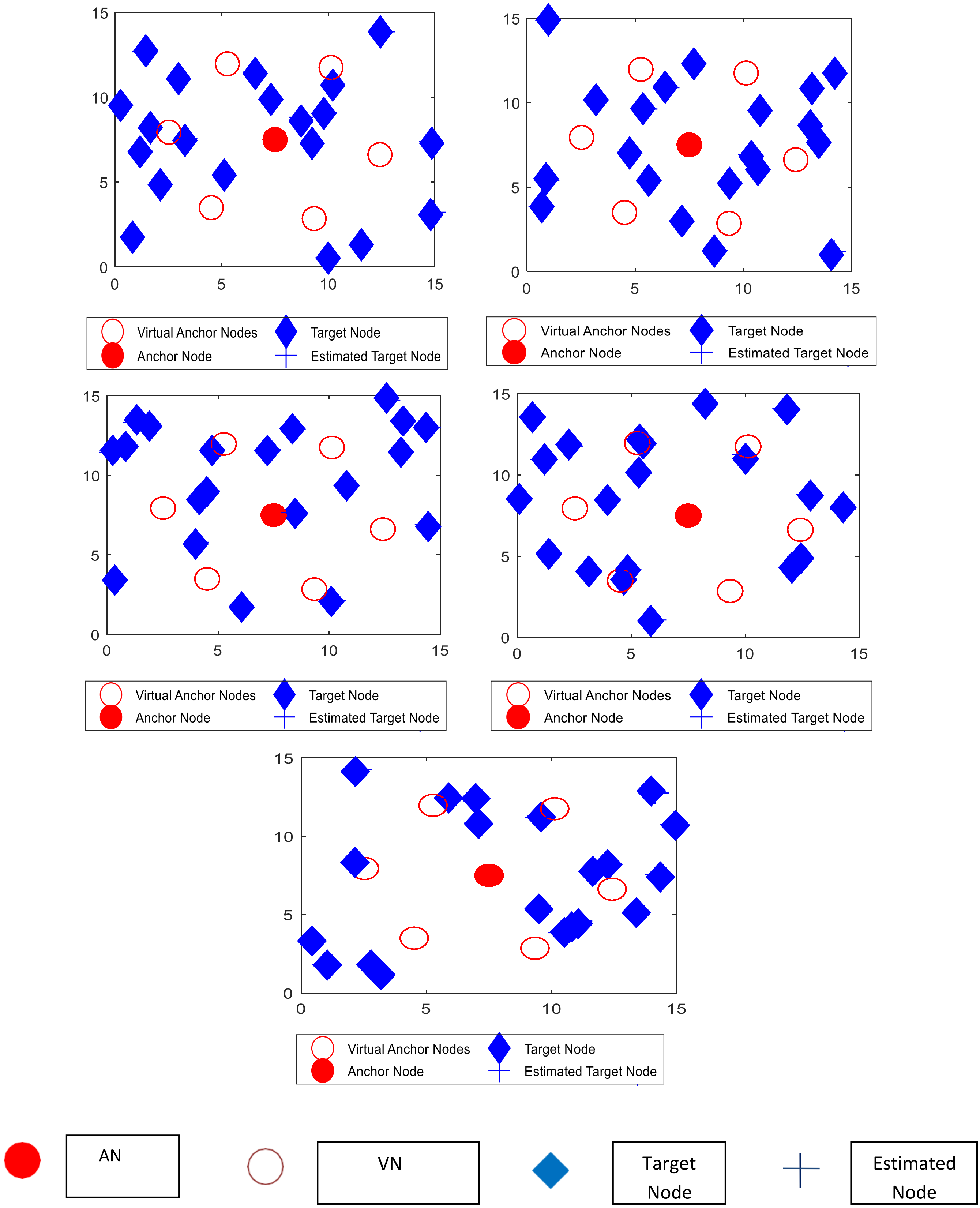
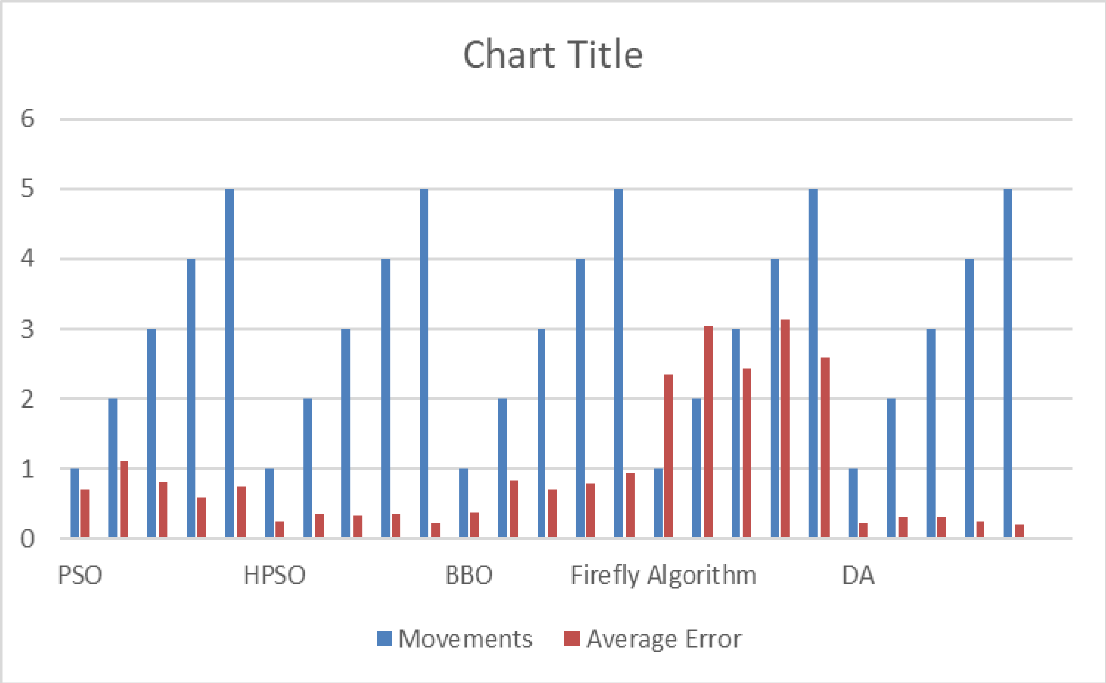


Figure 3.5: DA localization approach under various movements



Comparison of ALE of DA with existing techniques

3.4 NODE LOCALIZATION USING NNA

A new algorithm for optimization based on NN called NNA is created [184]. NNA is a meta-heuristic approach with which the end-users are not required to alter any parameter. Artificial Neural Networks (ANNs) reduce mean square error by iteratively updating the weights and correlating the input with the output.

NNA's follows ANNs. A "pattern solution" is a one-dimensional vector that represents the NNA's input data. A "pattern solution" refers to every individual searching agent community wise.". $Pattern\ Solution_i = [x_{i,1}, x_{i,2}, x_{i,3}, \ldots, x_{i,D}]$.

In NNA, a pattern solution matrix X of dimensions $N_{pop} \times D$ is created at random between the search space's lowest and upper boundaries. Population X is represented by Equation (3.15).

$$X = \begin{bmatrix} X_1 \\ X_2 \\ . \\ . \\ . \\ X_{N_{pop}} \end{bmatrix} = \begin{bmatrix} x_{1,1} & x_{1,2} & x_{1,D} \\ x_{2,1} & x_{2,2} & x_{2,D} \\ . & . & . \\ . & . & . \\ . & . & . \\ x_{N_{pop},1} & x_{N_{pop},2} & x_{N_{pop},D} \end{bmatrix} \tag{3.15}$$

where

$$x_{ij} = LB_j + rand(UB_j - LB_j), i = 1, 2, \ldots, N_{pop}, j = 1, 2, \ldots, D \tag{3.16}$$

Here, *LB* and *UB* are 1×D vectors indicating the search space's bottom and upper limits.

In NNA, every pattern result X_i is having matching weight W_i, similar to ANNs.

$W_i = [w_{i,1}, w_{i,2}, w_{i,3}, \ldots, w_{i,N_{pop}}]^T$

Array weights W is represented with Equation (3.17).

$$W = \left[W_1, W_2, \ldots, W_i, \ldots, W_{N_{pop}}\right] = \begin{bmatrix} w_{11} & w_{i1} & \cdots w_{N_{pop}1} \\ w_{12} & w_{i2} & \cdots w_{N_{pop}2} \\ . & . & . \\ . & . & . \\ . & . & . \\ w_{1N_{pop}} & w_{iN_{pop},2} & \cdots w_{N_{pop}N_{pop}} \end{bmatrix} \tag{3.17}$$

where W represents a matrix of $(N_{pop} \times N_{pop})$ that is distributed uniformly in random fashion between 0 and 1.

Random values are assigned as NNA's starting weights, and are updated as the iteration progresses conceptualized on the error transmitted in the network. The gross weight of the pattern solution should not go more than one; hence, the weight values are assigned. Weight pattern solution is mentioned as follows:

$$w_{ij} \in \mathcal{U}(0,1), i, j = 1,2,3, \ldots, N_{pop} \tag{3.18}$$

$$\sum_{j=1}^{N_{pop}} w_{ij} = 1, i = 1,2,3, \ldots, N_{pop} \tag{3.19}$$

Each pattern solution's fitness C_i is determined by evaluating the objective function f_{obj} the associated pattern solution X_i.

$$C_i = f_{obj}(X_i) = f_{obj}(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{iD}), i = 1,2,3, \ldots, N_{pop} \tag{3.20}$$

The pattern result with the best fitness is regarded the target result, with a target position X^{Target}, target fitness F^{Target}, and target weight W^{Target} after the fitness calculations for all pattern solutions. The NNA simulates an ANN through N inputs, also which has D dimensions, and only single target output, X^{Target} .

The new pattern solution is developed and given as by Equations (3.21) and (3.22).

$$X_j^{New}(k+1) = \sum_{i=1}^{N_{pop}} w_{ij}(k).X_i(k), j = 1,2,3, \ldots, N_{pop} \tag{3.21}$$

$$X_i(k+1) = X_i(k) + X_i^{New}(k+1), i = 1,2,3, \ldots, N_{pop} \tag{3.22}$$

Where, iteration index is represented by k.

Updated Weight Matrix Equation (3.23) is given below:

$$W_i^{Updated}(k+1) = W_i(k) + 2.rand.(W^{Target}(k) - W_i(k),), i = 1,2,3, \ldots, N_{pop} \tag{3.23}$$

During the optimization process, the constraints (3.16) and (3.17) must be met.

The recommended algorithm includes a bias operator for better search space exploration which adjusts updated weight matrix $W_i^{Updated}(k+1)$ as well as a fixed range of the pattern results developed in new population $X_i(k+1)$. It also avoids premature convergence by instructing a subset of the population to investigate areas of the search space that have yet to be explored by the population.

A modification factor β_{NNA} determines the percentage of pattern results that will be changed utilizing the bias operator. β_{NNA} initially was 1, indicating to entire population is prejudiced. β_{NNA} shall correspondingly be decreased at every iteration with accessible reduction mechanism, as given below by Equations (3.24) and (3.25).

$$\beta_{NNA}(k+1) = 1 - \left(\frac{k}{Max\ iteration}\right), k = 1,2,3, \dots, Max\_iteration \quad (3.24)$$

$$\beta_{NNA}(k+1) = \beta_{NNA}(k).\alpha_{NNA}, k = 1,2,3, \dots, Max\_iteration \quad (3.25)$$

where α_{NNA} a positive value is less than 1, initially set at 0.99.

The modification factor β_{NNA} is reduced to improve the method's exploitation as the number of iterations increases by allowing the algorithm to find the best solution that is close to the objective solution, mainly in the last iterations.

The following Equation (3.26) describes the Transfer Function operator (TF).

$$X_i^*(k+1) = TF\big(X_i(k+1)\big) = X_i(k+1) + 2.rand.\big(X^{Target}(k) - X_i(k+1)\big),$$
$$i = 1,2,3, \dots, N_{pop} \quad (3.26)$$

The ith updated pattern solution$X_i(k+1)$ is transported to updated position $X_i^*(k+1)$ from the last one pointing target pattern solution $X^{Target}(k)$ using the transfer function operator.

Also, in NNA, the bias operator is more likely to generate a new pattern result at the beginning of the iteration process, which means more opportunities for discovering previously unseen pattern solutions and experimenting with new weight values. The probability of applying the bias operator reduces as the number of iterations increases, whereas the Transfer Function (TF) operator increases, boosting the exploitation of the NNA, especially during the last iterations.

Because the creation of a new updated result (as specified in Equation (3.27)) is dependent on all of the population specified mathematically therefore NNA is called a dynamic optimization model:

$$X_i(k+1) = f(X_i(k), X(k)), i = 1,2,3, \dots, N_{pop} \quad (3.27)$$

The procedure to find target nodes are:

a) In a 15x15 m^2 area, one AN with a number of TNs is installed.

b) When a mobile node (target) comes close to an AN, each TN preserves a distance table between the two and two virtual AN's in the area (since at least three nodes are required for locating TN's). Figure 3.10 depicts the concepts of AN, VN, and TN.

c) The NNA approach is utilized to track down TN's position.

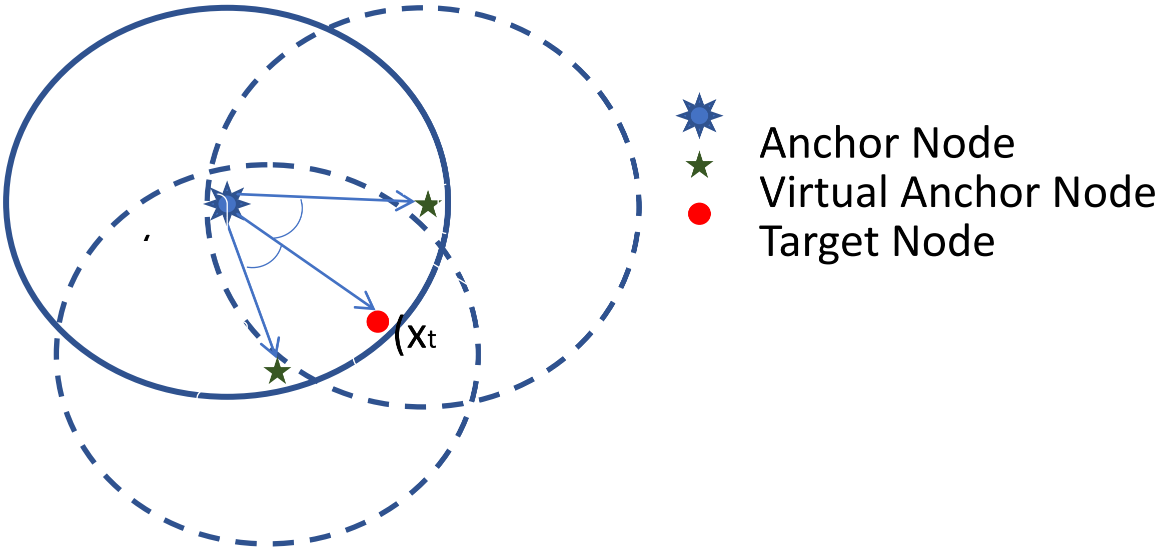


Figure 3.6: Diagram of a sensor field

Each movable TN and AN is depicted in Figure 3.6 and the distance is measured using the Equation (3.28).

$$d_i = \sqrt{(x_t - x)^2 + (y_t - y)^2} \quad (3.28)$$

where (x_t, y_t) are TN positions, (x, y) is the current position of AN. Centroid (x_c, y_c) is discovered (as specified by Equation 3.29) and presented as in Figure 3.7.

$$x_c, y_c = \left(\frac{x + xv_1 + xv_2}{3}, \frac{y + yv_1 + yv_2}{3}\right) \quad (3.29)$$

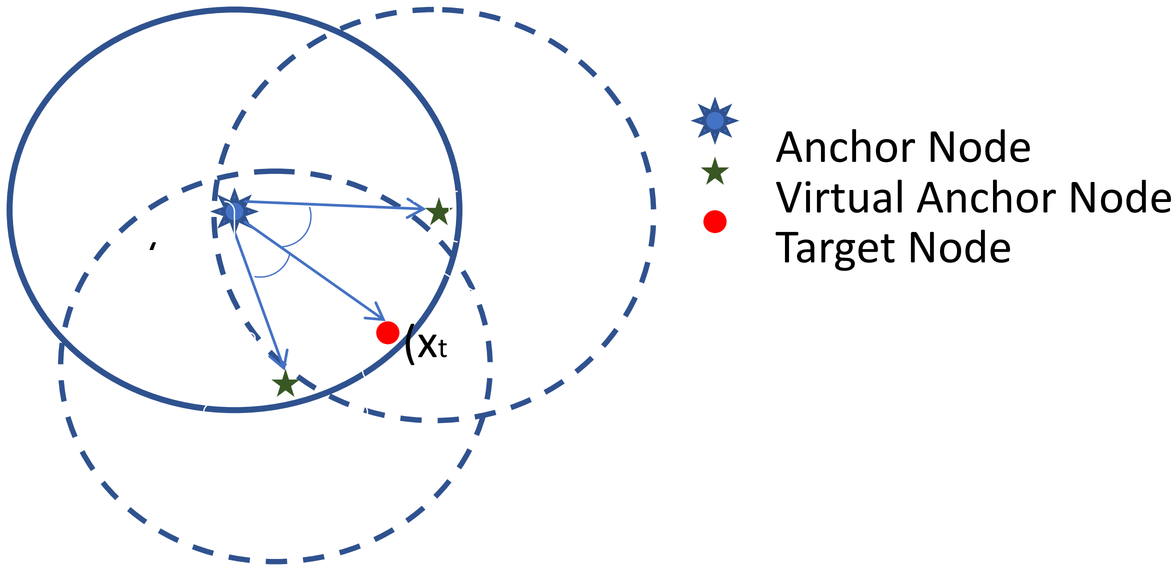


Figure 3.7: Centroid ANs and VNs computation

Figure 3.8 shows how NNA is utilized to identify TN's coordinates, which are recognized by (x_s, y_s). The concept is to reduce the distance between the actual node and computed coordinates, which is stated in Equation (3.30).

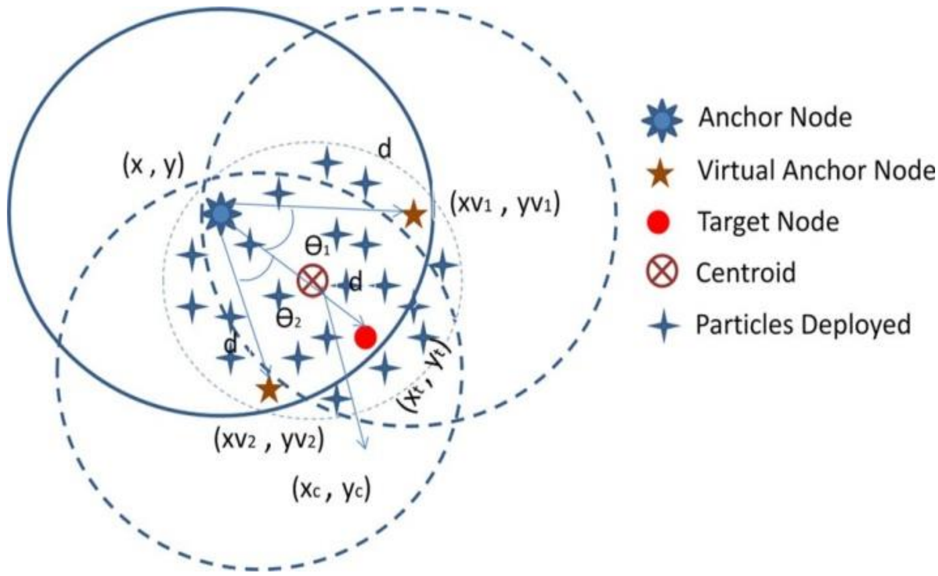


Figure 3.8: Implementation of NNA in the vicinity of the centroid

$$f(x_s, y_s) = \frac{1}{M} \sum \left(\sqrt{(x_e - x_i)^2 + (y_e - y_i)^2} - \hat{d}_i \right)^2 \tag{3.30}$$

Here, (x_e, y_e) represents the estimated position of the TN, (x_i, y_i) depicts the I location of the beacon node, which is positioned near to the target node, and M (M>3 here) depicts the total number of beacons. The Equation (3.31) discovers the localization error, which is depicted in Figure 3.9.

$$E_t = \frac{1}{N_L} \Sigma \sqrt{(x_e - x_t)^2 + (y_e - y_t)^2} \tag{3.31}$$

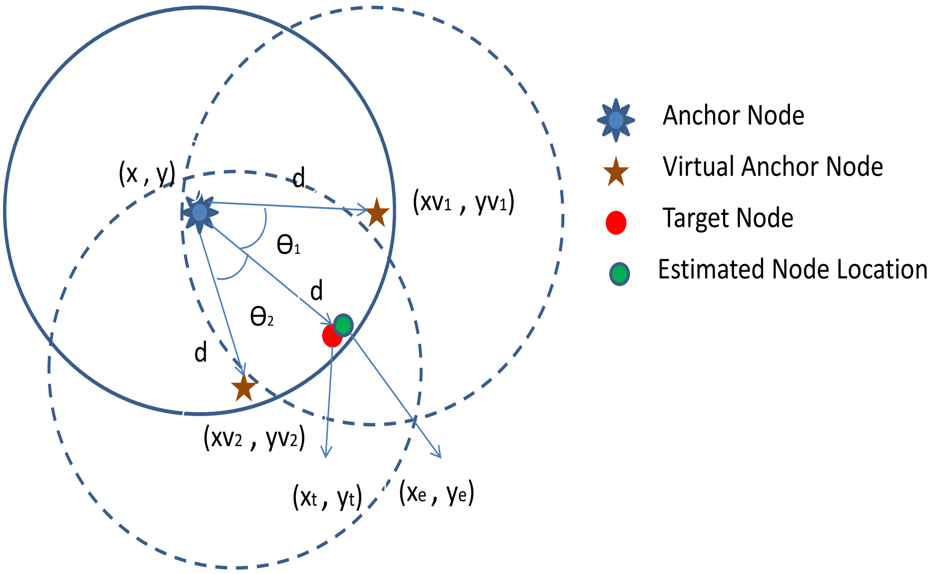


Figure 3.9: Estimated error using NNA

NNA evolves the best target node placement until the termination requirements are met (or the minimum value E_t is attained).

3.5 RESULTS AND ANALYSIS FOR NNA

Matlab is the tool with which the mentioned technique has been implemented. The simulations were done on a Windows computer having an Intel i3 processor and 8GB of RAM. One AN along with the help of two VN's is able to trace the TN. Total six VN's could be used but we are using only two as at least three nodes are required to locate the target node. Therefore to reduce the complexity we are using only two VN's. On a 15x15 m network, simulations were run. The sensing field having dimensions (7.6 x 7.6 m) contains the AN in the middle, while twenty target nodes are strewn over the sensing region. The coordinates of AN and VN are shown in Table 3.4. The distance between the Anchor and the target nodes has been illustrated in

Table 3.5. It can also be visualized through Figure 3.10 where it has been represented graphically. This has been achieved due to the adaptive unsupervised method of NNA for solving optimization problems.

Symbolizing the variables as: AN-Anchor Node, TN- Target Node and VN-Virtual Anchor Node

Table 3.4: AN and VN position values for NNA

Coordinates	AN	VN1	VN2	VN3	VN4	VN5	VN6
X	7.6	10.116	5.248	2.508	4.497	9.315	12.399
Y	7.6	11.845	11.877	7.898	3.502	2.903	6.598

Table 3.5 represents that 20 TNs with a single anchor node and six VN are deployed in the sensing field.

Table 3.5: Distance between anchors and targets for NAA

S.No	Anchor	VN-1	VN -2	VN -3	VN -4	VN -5	VN -6
T N-1	4.81950833	7.97531255	9.65632634	8.82276928	6.11755065	1.65671265	3.42654076
TN-2	4.25851103	4.36430216	7.7394740	9.13328368	8.28970901	5.3881682202	1.400260626
TN-3	8.5008735	8.300563987	3.76985402	6.20184637	10.9005635	13.40083502	12.68929545
TN-4	2.88929145	6.38511197	7.90114601	7.50107102	5.28913699	2.489995240	3.200617112
TN-5	8.38870699	4.10005499	8.87174101	12.500056	13.2892601	11.15818198	6.500737897
TN-6	4.88950201	3.18893201	1.80072399	6.28958699	9.18875299	9.788026899	7.889525901
TN-7	4.68968299	7.40124402	9.60193911	9.3000610	6.58956802	2.401491899	2.600117902
TN-8	4.30039410	0.8565498	4.40188899	7.80107910	9.3016485	8.400907298	5.380450502
TN-9	8.70012402	13.5002802	11.1012899	6.40149901	3.90040102	8.400424702	12.40032899

TN-10	6.40045110	7.40178899	10.5898399	11.3005798	9.10189102	4.587013899	1.689306699
TN-11	6.78947601	6.10160610	10.2006699	11.7865732	10.6005502	6.801576201	2.101561291
TN-12	5.20083835	4.30187799	0.80018799	5.58803802	9.10142342	10.20416246	8.801607601
TN-13	7.38934864	12.4008636	10.5015068	6.24210532	2.38929863	6.720503386	10.80198624
TN-14	7.7000363	12.7000853	11.1010565	6.90061960	2.70206832	6.40104576	10.80123752
TN-15	4.80149901	4.20081902	7.88983201	9.80108599	9.10054640	6.100281902	1.600691482
TN-16	4.70101799	7.60010670	9.60024094	9.10105693	6.40051184	2.009539835	2.975462578
TN-17	8.08929335	4.88972836	9.68999799	12.6895792	12.7004989	9.701289775	4.80181335
TN-18	3.28929635	3.200947790	2.20072140	5.40098056	7.68996871	8.300812588	6.800570825
TN-19	8.18857681	12.946322	9.88945264	5.10108589	4.10187231	8.88919201	12.50133791
TN-20	5.38902139	8.70380340	4.80765821	0.6239412	5.28406879	9.127390165	10.38628467

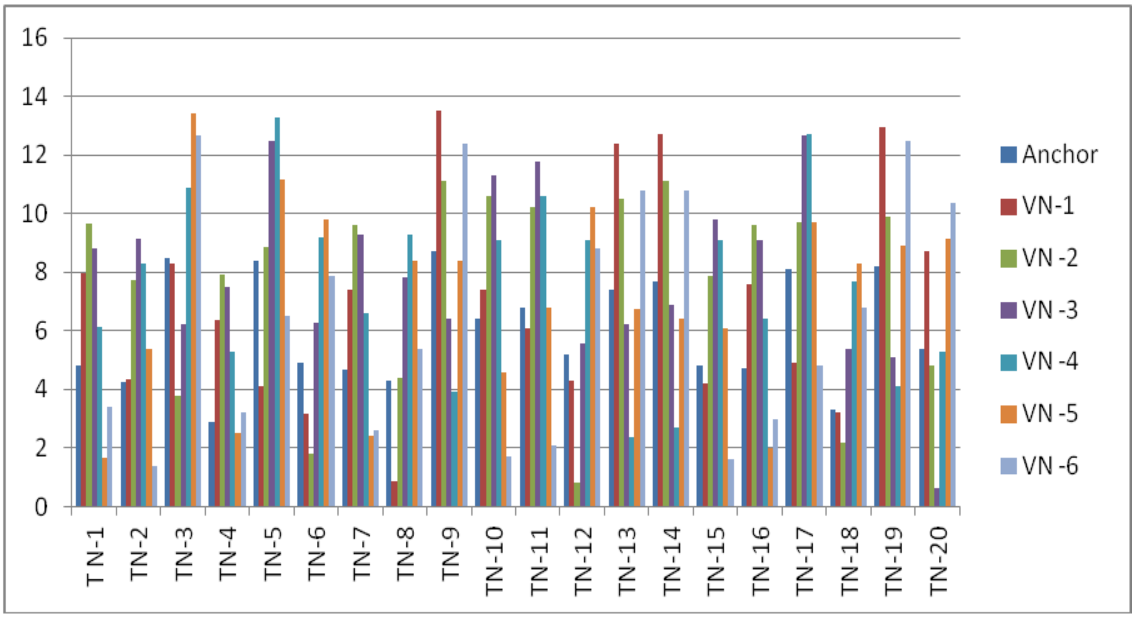


Figure 3.10: Graphical representation of distance between anchor and targets

Table 3.6 presents various optimization techniques to localize the moving target nodes in the sensing field for five movements within a range of 10 meters corresponding to average localization error.

Table 3.6: Comparison of algorithms for calculating localization error for NNA

Algorithms	Movements	Transmission Range	Maximum Localization error(m)	Minimum Localization Error(m)	Average Error(m)
PSO [183]	1	10	1.8674	0.1431	0.6944
	2	10	3.8233	0.2142	1.1234
	3	10	2.6978	0.1241	0.8132
	4	10	1.8914	0.2132	0.5878
	5	10	1.7897	0.1698	0.7432
HPSO [183]	1	10	0.6827	0.1188	0.2445
	2	10	0.7623	0.0963	0.3532
	3	10	0.7336	0.0481	0.3334
	4	10	0.6591	0.2189	0.3487
	5	10	0.5271	0.2187	0.2205
BBO [183]	1	10	1.4713	0.0321	0.3834
	2	10	1.4797	0.0779	0.8223
	3	10	1.4714	0.0363	0.6922
	4	10	1.4854	0.0442	0.7980
	5	10	1.6714	0.0582	0.9313
FA [183]	1	10	4.6765	0.3834	2.3590
	2	10	5.8855	0.5865	3.0534

	3	10	4.8872	0.0323	2.4408
	4	10	5.2234	0.2454	3.1356
	5	10	4.6678	0.1980	2.5820
NNA (Proposed)	1	10	0.5827	0.1088	0.1145
	2	10	0.6423	0.0793	0.2132
	3	10	0.6236	0.0181	0.2034
	4	10	0.5491	0.1889	0.1387
	5	10	0.4031	0.1778	0.1005

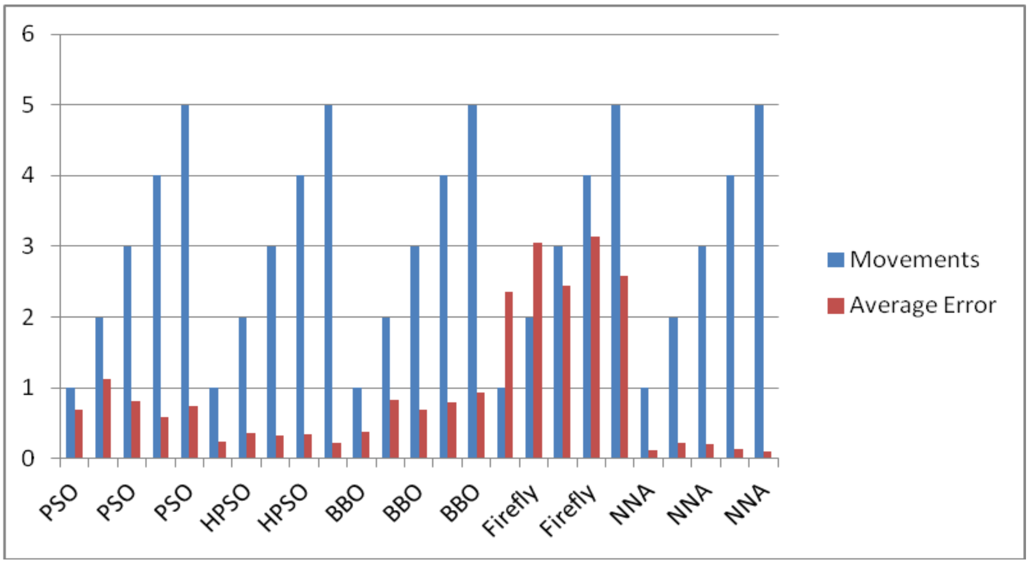


Figure 3.11: Comparison of Average Localization Error of existing techniques with NNA

Figure 3.11 shows that the localization error for NNA is quite low. In this case, the node position is determined in NNA with the least amount of localization error and the quickest processing time possible.

Figure 3.12 shows that the localization error for NNA is quite low and also, as inferred from Table 3.6, comprises its contrast with other approaches. Here, the node position is determined in NNA with fewer amounts of localization errors and the quickest processing time possible.

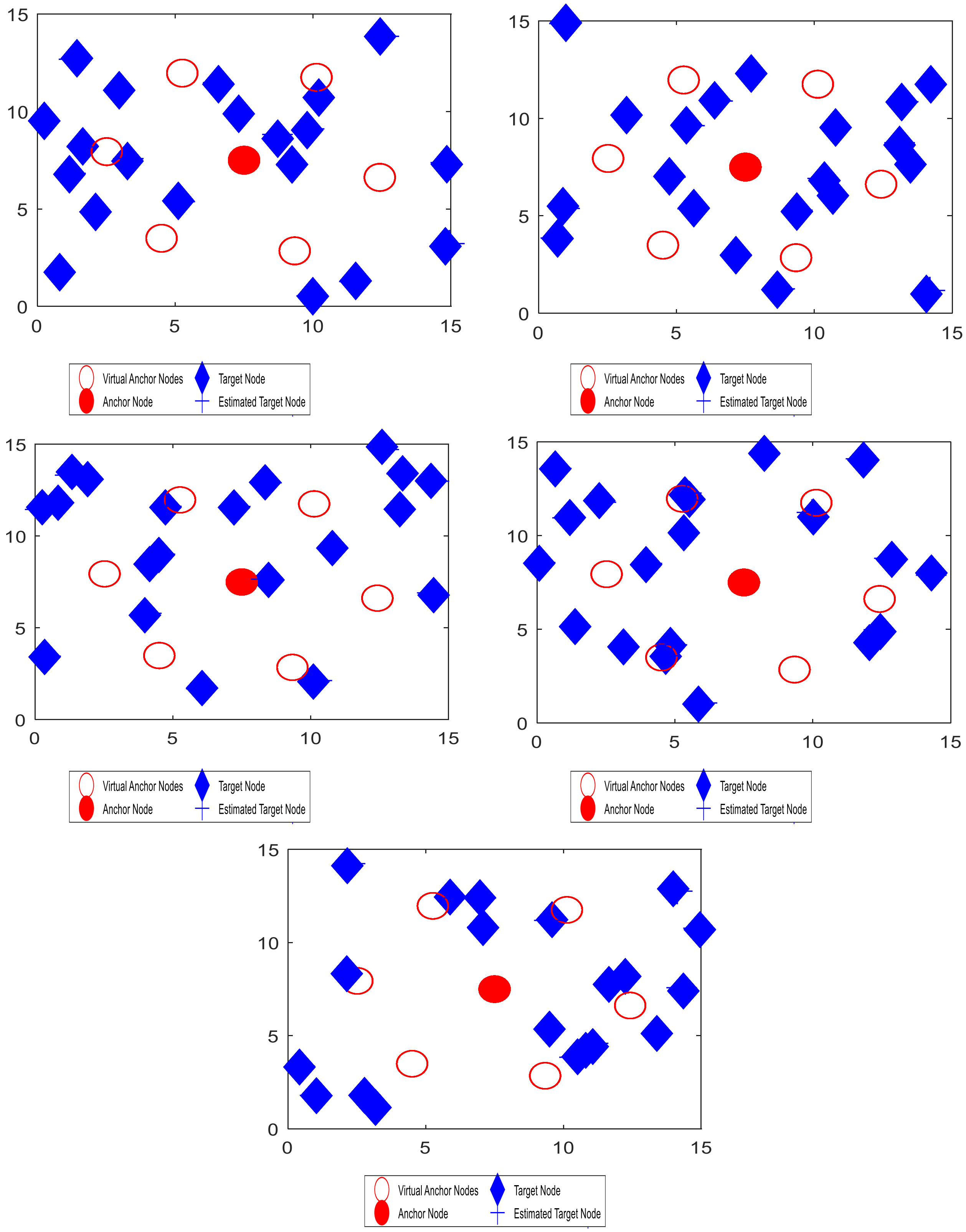


Figure 3.12: NNA localization techniques under various movements

3.6 CONCLUSION AND FUTURE SCOPE

The work proposed in this chapter is the DA metaheuristic optimization localization technique for identifying locations of randomly arranged target nodes. There are two aspects to the location computations. To begin, the anchor and the target node distance is calculated after the notion of VN's is proposed, with VN's is being placed at certain angles in the field at a defined distance between the anchor and the target node. Then centroid is calculated, and DA is used to compute the localization error. The method described and proposed is used in a variety of applications, including logistics and military. In 3D localization, DA can also be used to determine 3D coordinates. The exploration ability boosts up the accuracy and efficiency which at the same time results in error reduction . The same has been verified by the comparison of our results with the existing algorithms This chapter presents another method named NNA meta-heuristic optimization localization technique to find locations of randomly organised target nodes. The computations of location have two components. After calculating the distance between AN and TN, the notion of VNs is offered, with VNs positioned in the field at certain angles and a set distance among both the nodes. The centroid is determined, and the localization error is estimated using NNA. The aforementioned strategy is employed in a range of applications, including logistics and military. The concept of NNA can also be utilized in 3D localization to find the nodes' exact location. To improve the findings, hybrid optimization strategies can be applied in the future.

CHAPTER -4

LOCALIZING MOBILE NODES IN RANGE BASED 3D HOMOGENEOUS WSN USING METAHEURISTIC ALGORITHM

In 3D landscapes, sensors are put in mountains for tracking and in the air for pollution monitoring. Such applications cannot rely on 2D localization models. This presents additional issues for the design of 3D localization systems in WSNs. In this chapter, a single anchor node is utilized to locate unknown nodes in a 3D environment. In a simulation-based environment, the middle and lower levels include nodes with uncertain positions, whereas the top layer has a single anchor node. Adaptive Plant Propagation Algorithm (APPA) is a revolutionary soft computing approach presented to determine the optimal placements of these mobile nodes. These mobile target nodes are diverse and have been deployed in an anisotropic environment with a DOI value of 0.01. Simulation findings demonstrate that the proposed APPA method outperforms previous meta-heuristic optimization strategies in terms of localization error, computational time, and the sensor nodes that are located.

4.1 INTRODUCTION

Wireless Sensor Networks (WSNs) contain many small low-power sensor nodes (SNs) deployed randomly in the environment to determine the physical behavior. Sensors are often used to obtain measurements of location, temperature, humidity, irradiance, sound, and pressure [184]. In most of WSNs applications, location determination is crucially important and sensor nodes deployed in these areas are of utmost importance as no one is present in the field to locate and place the nodes personally. So, in these applications, sensor nodes are randomly deployed at unknown locations, and they adopt random locations in the sensor field. On the other hand, the exact location is not known of an occurring event the information gathered by these sensors is useless [185]. To locate the sensor nodes in WSN, GPS, which is one of the most widely used techniques for localization, was developed to overcome the limitations of previous navigation systems [186]. GPS is being used in military, industry, and, more recently, consumer/civilian applications. However, GPS does not work with obstacles that limit LOS communications between the satellites and the GPS receiver; therefore, its utility is limited in dense forests, mountains, and also in indoor environments. To overcome GPS limitations, sensor networks can be applied for localization. An alternative way to find out all unknown nodes in the scenario is to deploy a few sensors within built GPS features that are known as anchor nodes. Thus, the exact location of these sensors is known after deployment in WSNs. By using the known locations of these anchors, many methods already available in the literature are used for the evaluation of the location of unknown nodes (or unknown nodes). Range-based and Range-free algorithms are different algorithms that exist in the literature. The first one measures the distance between nodes using RSSI, AoA, and ToA [186-187]. Thus, range-free strategies, distance vector hop, multidimensional signaling, and Adhoc positioning system provide the location of various targeted nodes with fewer infrastructure requirements. In WSN, providing exact localization is one of the greatest problems. Localization can be done precisely in static nodes, but it is much more difficult in moving nodes. We introduced the idea of using a novel APPA to target unknown nodes with the help of only one node, which is called the anchor, and an assumption is taken about this node virtually in six different directions. Whenever the nodes whose location is to be found outcomes under the range of anchor, virtual anchors are placed at 60 degrees angles, with the same range as that of anchor, and out of the six, only three nodes are nominated to trace the exact position of the unknown node because at least four SNs are needed to find out three-dimensional positions. Here, we are working to find out the evaluation and hence efficiency of localization problems with various meta-heuristics using APPA.

4.2 ADAPTIVE PLANT PROPOGATION ALGORITHM (APPA)

This algorithm is comprised of a population of shoots, and every shoot presents a solution in the search space. It is assumed that each shoot has taken root, which is equivalent to the objective function being assessed. Each shoot will then send runners out to explore the space around the solution.

A plant is considered to be in a location $Y_i = \{y_{i,j},\ j = 1, 2, \dots, n\}$where the dimension of the search space is given as n. Let the population size be denoted as $N_p$which determines the number of strawberry plants to be used initially. It is known that strawberry plants which are in poor spots propagate by sending long runners which are few in number, the process being known as exploration. The plants which are in location with abundance of essential nutrients, minerals and water propagate by sending many short runners, the process is known as exploitation. Maximum number of generations considered is g_{max} and maximum number of permissible runners per plant is n_{max}.

The objective function values at different positions $Y_i, i = 1, 2, \dots, N_p$are calculated. These possible candidate solutions will be sorted according to their fitness scores. Here the fitness is a function of value of the objective function under consideration. It is better to keep the fitness scores within ascertain boundary between 0 and 1, that is, $f(x) \in [0, 1]$. To keep the fitness values within this range, a mapping is done using the sigmoid function, described by Equation (4.1)

$$N(x) = \frac{\exp\left(\frac{(f(x))}{\max\ (f(x))}\right)}{1 + \left(\exp\left(\frac{(f(x))}{\max\ (f(x))}\right)\right)} \tag{4.1}$$

The effect of this mapping function is that, it provides a means of emphasizing further better solutions over those which are not as good.

The number of runners that are found out by the solution and the distance of propagation of each of them are described. There exists a direct relation between the number of runners produced by a candidate solution and its fitness given by Equation (4.2).

$$n_r = \mathrm{ceil}(n_{max} N_i r) \tag{4.2}$$

Here, n_r is the number of runners produced for solution iin a particular generation or iteration after the population is sorted according to the fitness given in Equation (4.2), n_{max} is the number of runners which is maximum permissible, $N_i$is the mapped fitness as determined using Equation (4.2), r is a random number lying between 0 and 1 which is randomly selected for each individual in every iteration or generation, and ceil refers to the ceiling function. The minimum number of runners is 1 and maximum is n_r. This function ensures that at least 1 runner should be there which may correspond to the long runner as described before. The distance of each runner is inversely related to its fitness as shown in Equation (4.3)

$$d_j^i = (1 - \mathrm{N_i})(\mathrm{r} - 0.5) \text{for } \mathrm{j} = 1,2, \dots \dots, \mathrm{n} \tag{4.3}$$

where n represents the dimension of the search space. So, each runner is restricted to a certain range between -0.5 and 0.5. The calculated distance of the runners is used to update the solution for further exploration and exploitation of the search space by the Equation (4.4).

$$\mathrm{x_{i,j}} = \mathrm{y_{i,j}} + (\mathrm{b_j} - \mathrm{a_j})\mathrm{d_j^i}, \text{for } \mathrm{j} = 1,2, \dots \dots, \mathrm{n} \tag{4.4}$$

The algorithm is modified to be an adaptive one in view of the limits of the search domain. Hence, the name is given as APPA. In the event that the limits are disregarded the point is changed in accordance to lie within the search space. Essentially, a_j and b_j are the lower and upper boundaries of the jth coordinate of the search space respectively. New plants are polled and the entire extended population is organized after every single individual plant in the population has passed on their designated runners. To keep the population fixed, rather than the size of the population fixed, it is to be guaranteed that the candidates with lower growth are dispensed from the population. Another strategy is adopted to avoid being struck in the local minima. It might happen that for a certain number of generations, there is no improvement in a candidate solution; rather the runners it sends out are also not fit to remain in the population. So a threshold to be set for such a solution such that if the number of generations in which it is not enhancing surpasses the threshold, then the solution is discarded, and another fresh candidate solution or individual is produced within the limits of the search space. The working of APPA has been represented in the form of Figure 4.1.

4.3 SINGLE ANCHOR NODE LOCALIZATION CONCEPT

In this 3D localization problem, a single anchor node with known location information is considered, and this location information of the anchor is utilized to find out the locations of randomly placed mobile nodes. These mobile nodes are grouped into three different layers with an anchor placed at the top most position, and unknown nodes are moving at the middle and the bottom layers. Anchor nodes transmit a beacon signal that will be sensed by mobile nodes, and using the concept of virtual anchors, three of these virtual anchors and the anchor node itself are selected to locate all the mobile nodes. Based on the received RSSI, the approximated distance between anchor and target node is estimated. A detailed description of localization using the APPA algorithm is given in Figure 4.2.

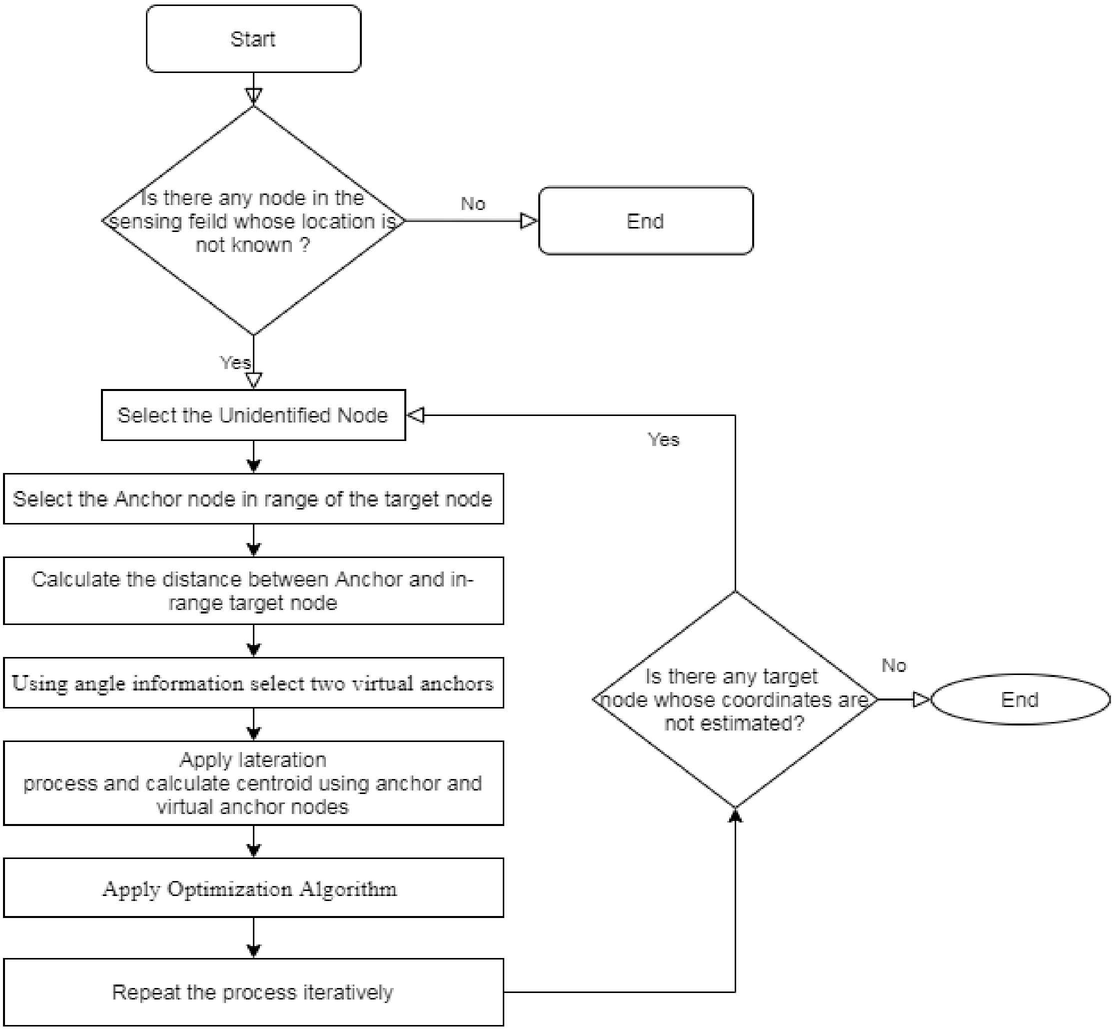


Figure 4.1: Flowchart of the Adaptive Plant Propagation Algorithm (APPA)

The proposed algorithm has below mentioned properties and further steps for estimating location information have been discussed in this section.

a) Using the APPA algorithm, a new method for projecting virtual nodes in the field to determine the exact locations of deployed sensor nodes in a three dimensional scenario.
b) LOS problems will be reduced to a greater extent with virtual anchor nodes.
c) Flip ambiguity issues in range-based methods are also minimized.

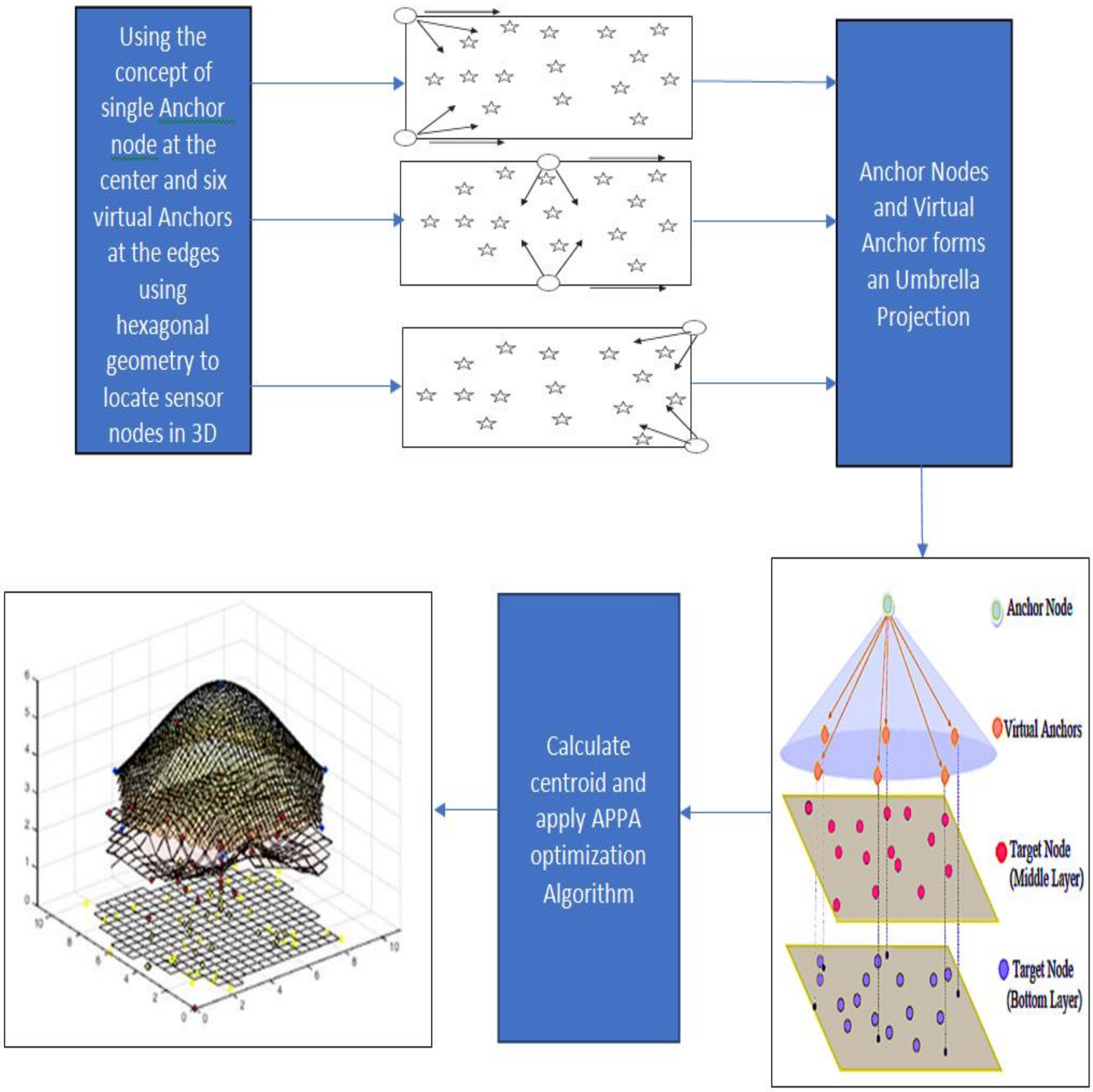


Figure 4.2: Detailed description of 3D Localization using APPA

Firstly, the anchor and moving target distance are determined in 3D scenarios using RSS measures. Further, the anchor nodes, which are virtual (six in number), are placed at the same distance at an angle difference of sixty degrees, as given in Figure 4.3. Here, for each target localization, an anchor with three virtual anchor nodes is selected in order to find coordinates in three-dimensional scenarios, respectively, as shown in Figure 4.4. This selection of virtual anchor nodes is made using directional information of the target node. The anchor and target node distance is given by Equation (4.5).

$$d_i = \sqrt{(x_t - x)^2 + (y_t - y)^2 + (z_t - z)^2} \tag{4.5}$$

Here in 3D, the coordinates of the nodes which are targets is provided by (x_t, y_t, z_t) and the current position of the anchor node is represented by (x, y, z) for 3D scenarios. Also, the centroid (x_c, y_c, z_c) is deduced by Equation (4.6) in 3D environments, and is inferred in Figure 4.5.

$$x_{c,}y_c, z_{c,}) = \left(\frac{x + xv_1 + xv_2 + xv_3}{3}, \frac{y + yv_1 + yv_2 + yv_3}{3}, \frac{z + zv_1 + zv_2 + zv_3}{3}\right) \tag{4.6}$$

It is being inferred by Figure 4.6 that proposed APPA is compute target node positions and is represented by$(x_{s,} y_s, z_{s,})$. The distance among the estimated and actual location of target nodes has been inferred through the objective function as depicted in Equation (4.7)

$$f(x_{s,}y_{s,}z_{s,}) = \frac{1}{M}\sum\left(\sqrt{(x_e - x_i)^2 + (y_e - y_i)^2 + (z_e - z_i)^2} - \hat{d_i}\right)^2 \tag{4.7}$$

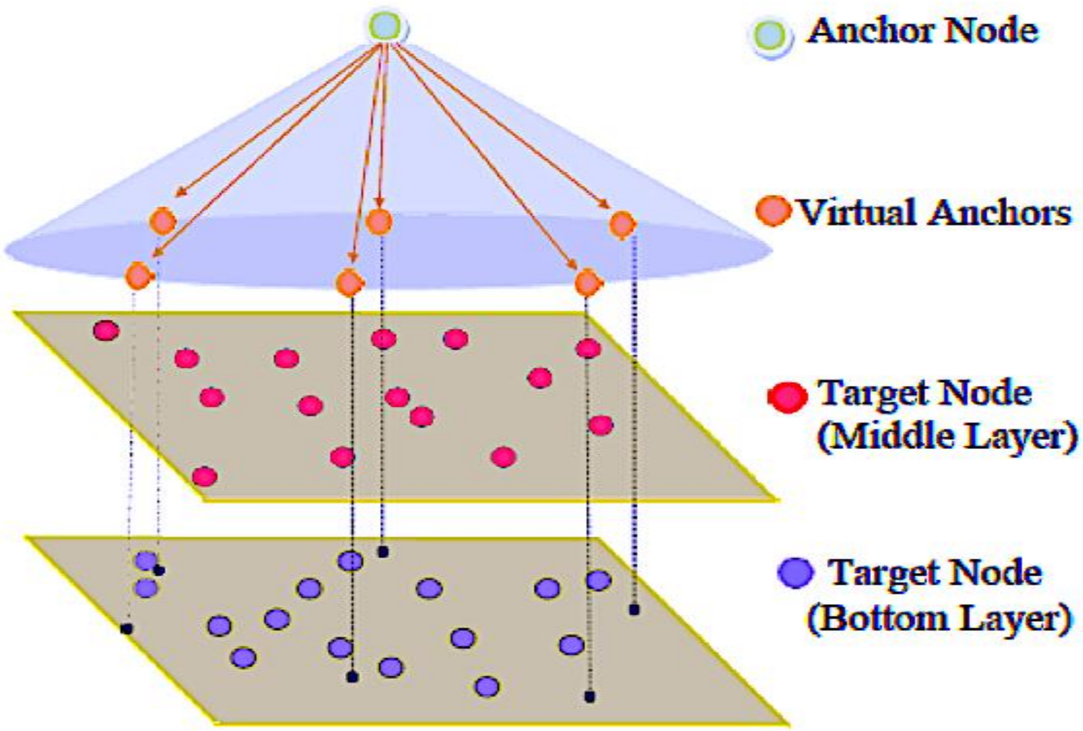


Figure 4.3: Umbrella projection to find out the position of mobile target nodes

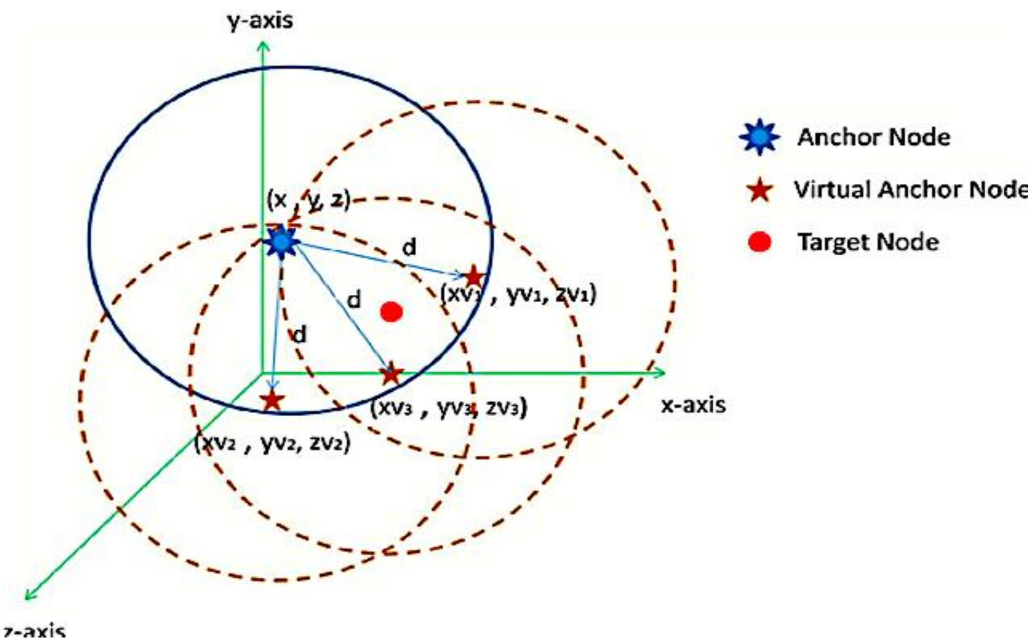


Figure 4.4: Sensor field in 3D environment with anchor and virtual anchor nodes

Here, the calculated position of the target node is represented by (x_e, y_e, z_e), calculated coordinates of the beacon node *i* and the target nodes is inferred by (x_i, y_i, z_i) (M > 4 to compute 3D location) respectively for 3D scenario.

Error in the process of localization is given by E_t, and is found out by Equation (4.8) and is shown in Figure 4.7 for three dimensional scenarios.

$$E_t = \frac{1}{N_L} \sum \sqrt{(x_e - x_t)^2 + (y_e - y_t)^2 + (z_e - z_i)^2} \tag{4.8}$$

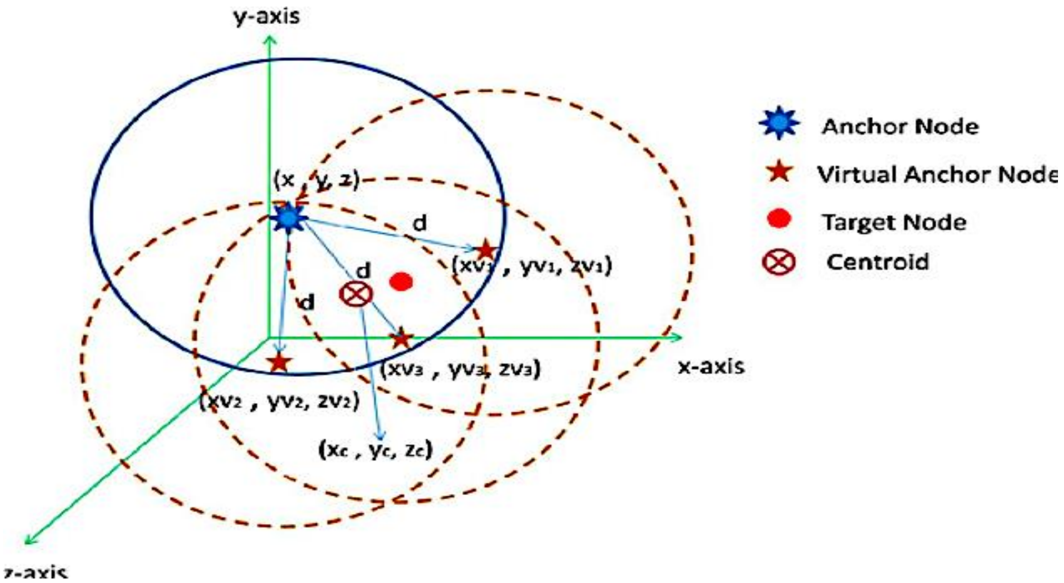


Figure 4.5: Three dimensional calculation using centroid

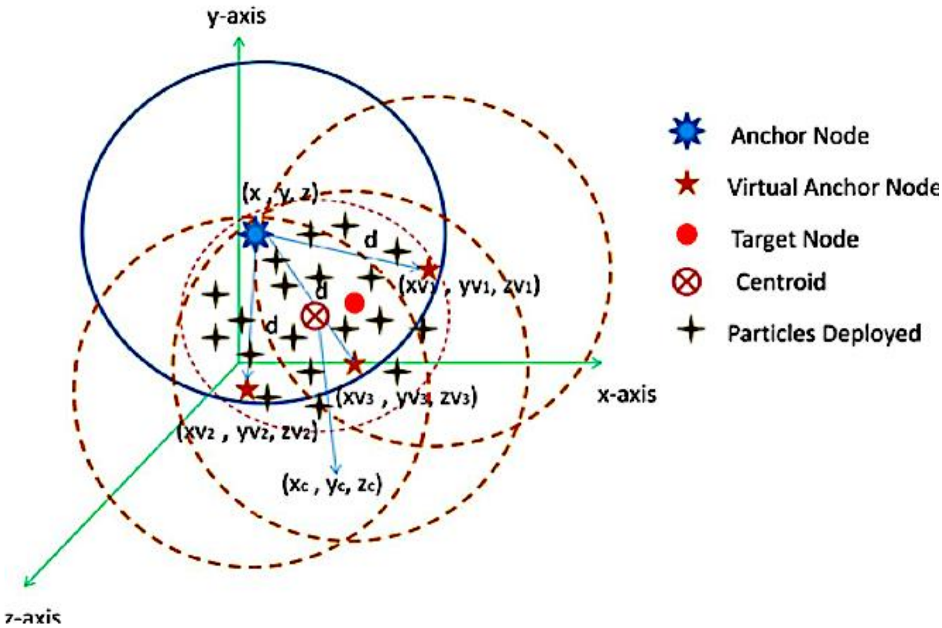


Figure 4.6: APPA particles deployed in 3D scenario

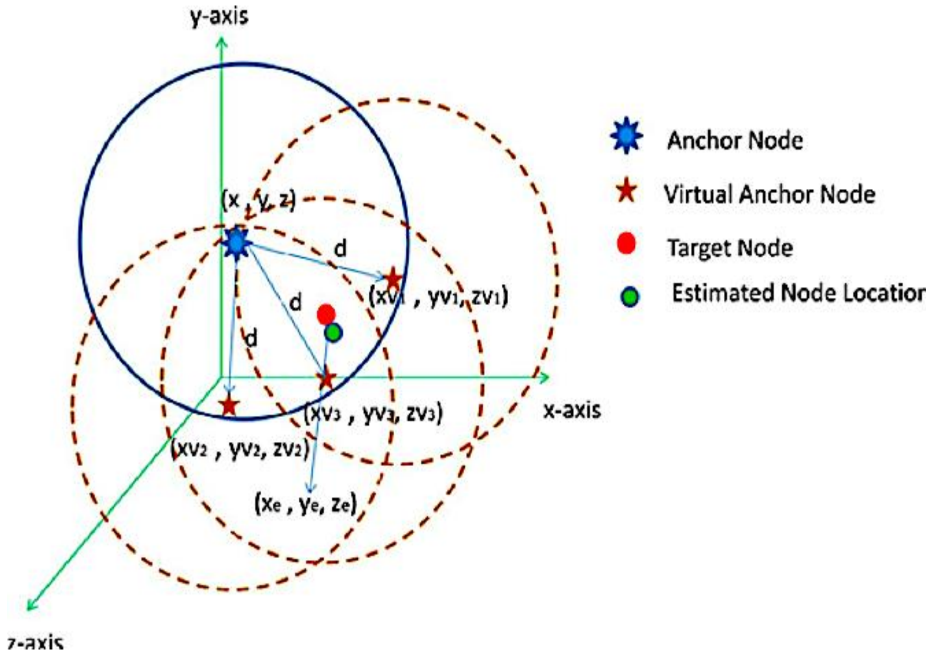


Figure 4.7: Estimated 3D location

4.4 SIMULATION RESULTS AND DISCUSSION

Here, a novel technique, APPA, is used for a three-dimensional localization problem where the concept of one anchor and six virtual anchors assumed in six directions placed is considered to find out the exact position of all unknown nodes. In three-dimensional environments, the structure is divided into different layers, normally three, and it is a cubic structure. Here the unknown nodes whose position is to be found are placed at the lower two layers, and the known nodes are kept at the topmost layer. The number of unknown nodes at each layer is kept to be forty. To find out the positions of the unknown nodes in three-dimensional environments, an umbrella projection is created. Deployment of more than six virtual anchors is also practically possible, but in 3D settings, just six virtual anchors are retained to find unknown nodes by picking only the four closest anchors. Table 4.1 lists the parameters needed by several meta-heuristic optimization techniques.

Table 4.1: Parameter settings

Algorithm	Parameters
PSO	*NP*=30; *D*=3; G_{max}=100; c_1, c_2, c_3=1.494; *w*=0.729
HPSO	*NP*=30; *D*=3; G_{max}=100; c_1, c_2, c_3=1.494; η=0.1; *w*=0.729
BBO	*NP*=30; *D*=3; G_{max}=100; p_m =0.05
FA	*NP*=30;*D*=3; G_{max}=100; $\alpha = 0.2$; $\gamma = 0.96$
GWO	*NP*=20;*D*=3; G_{max}=100; a= [2 to 0] ; C = [0 to 2]
APPA	*NP*=30;*D*=3; G_{max}=100; $n_{max} = 3$
TSNMRA	*NP*=30;*D*=2; G_{max}=50; $n_{max} = 3$

Here, *NP* is number of population, *D* is dimension of problem, G_{max} is number of iteration

Where (c1), (c2) and (c3) are the cognitive, social and neighborhood learning parameters. Here w is the inertia weight and Pm is the probability of mutation. In FA x and γ are randomizing and absorption coefficient. In mobility-based scenario, various optimization algorithms available in the literature are evaluated. Here the unknown nodes whose position is to be found out are placed at the lower two layers and the known nodes are kept at the top most layer. All the unknown nodes are moving while the anchor node is kept static. The average of the localization error given in Equation (4.8) is used to find out the fitness function. Figures 4.8, 4.9, 4.10, 4.11, 4.12 and 4.13 represent the output obtained by various optimized algorithms. The line of sight disadvantage is also reduced a lot with the help of assuming various nodes at different angles. It has been proved with the help of the results that using APPA, accurate locations are being found as compared to other algorithms and convergence characteristics are also faster. In future, with the help of hybridization of few optimized algorithms more accuracy could be achieved.

The average localization error for all competitive algorithms is computed in Table 4.2 and shown in Figure 4.14. When compared to other competitive algorithms tested for the same situation, APPA has a much faster convergence time.

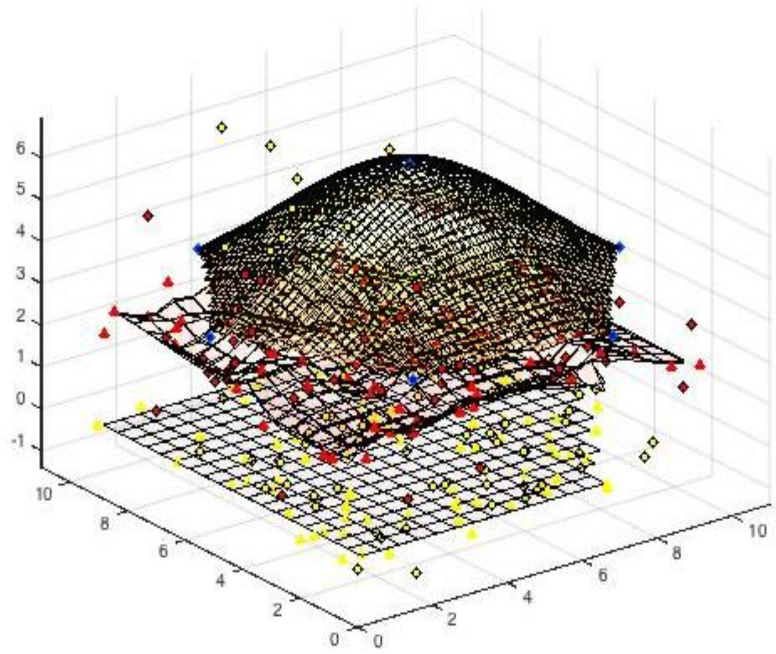


Figure 4.8: Representation of node movement through BBO

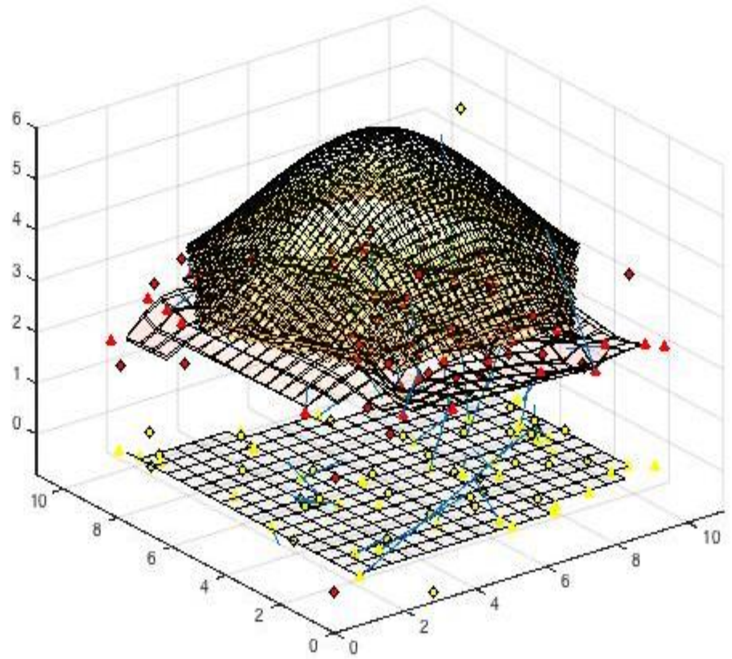


Figure 4.9: Representation of node movement through PSO

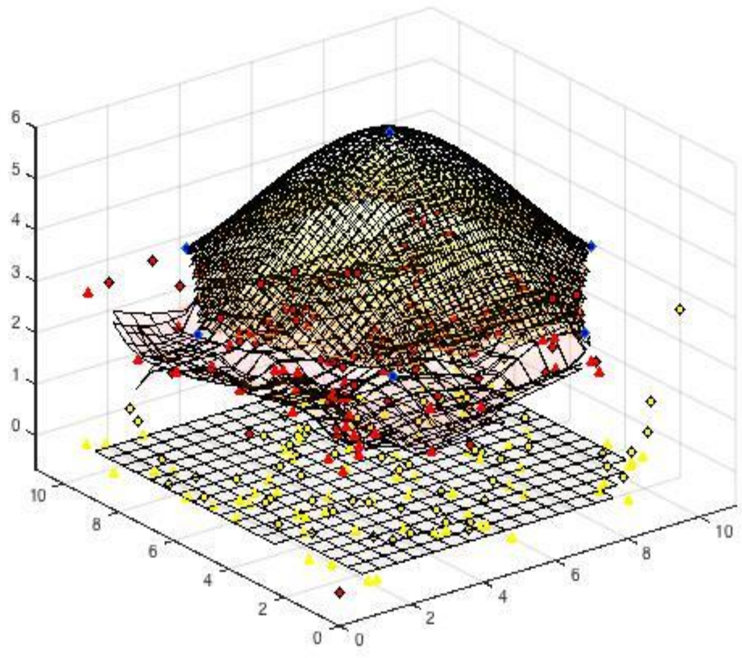


Figure 4.10: Representation of node movement through FA

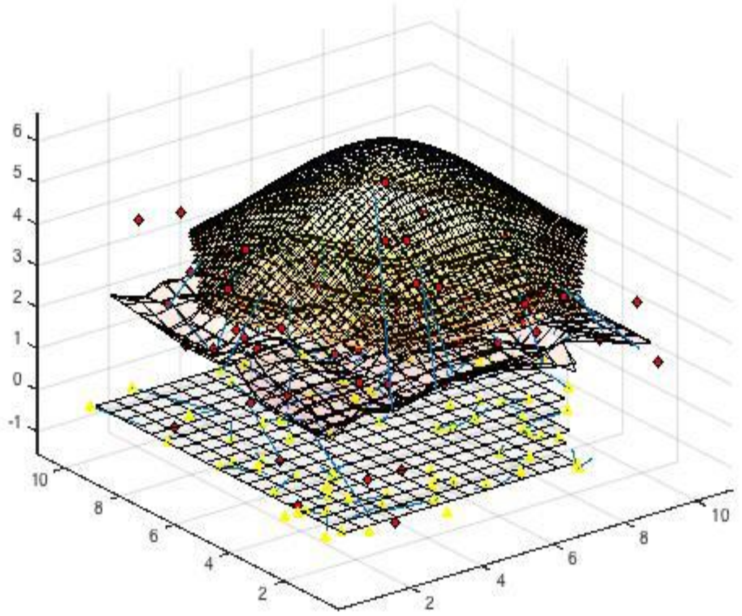


Figure 4.11: Representation of node movement through HPSO

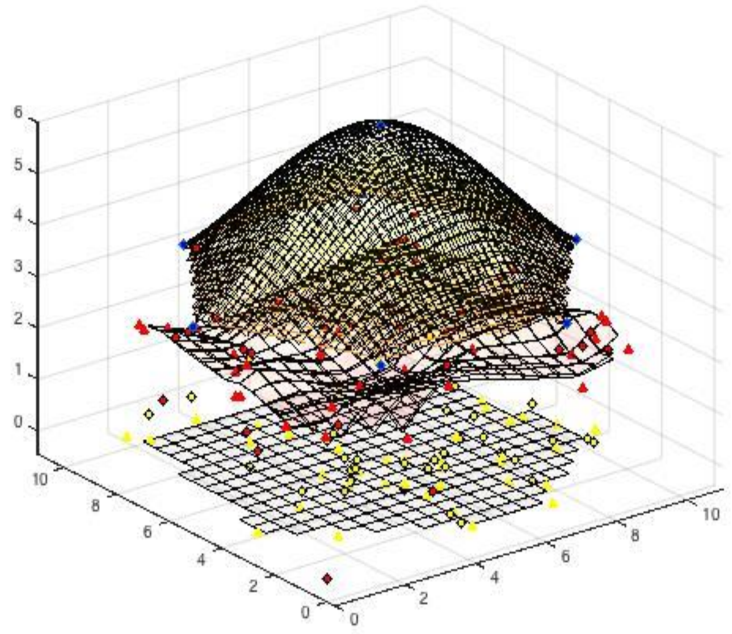


Figure 4.12: Representation of node movement through GWO

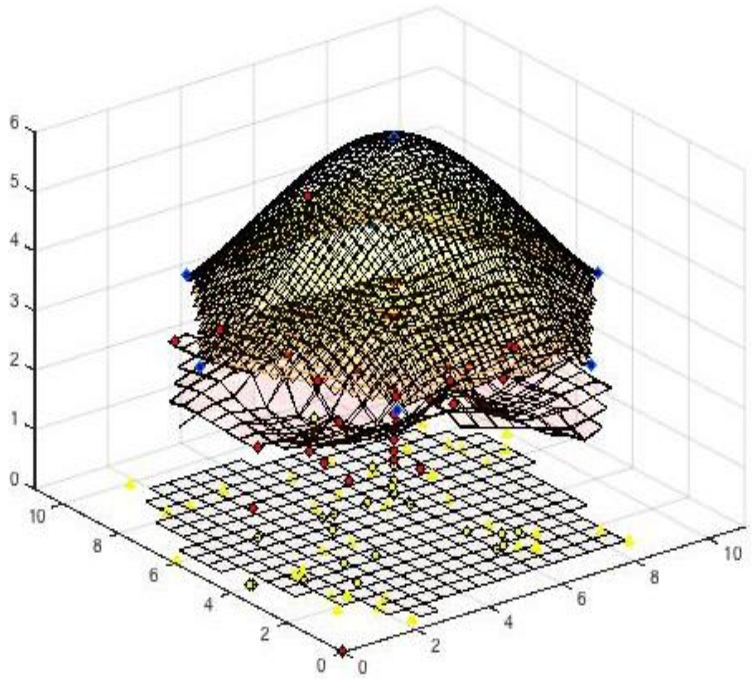


Figure 4.13: Representation of node movement through APPA

The localization optimization using algorithms viz. PSO, HPSO, BBO, GWO, and FA are already available in the literature with static scenarios. In this paper, these algorithms are also implemented with the proposed technique of having a single anchor node with umbrella-based projection. Further, these algorithms are compared with the APPA algorithm, given in Table 4.2.

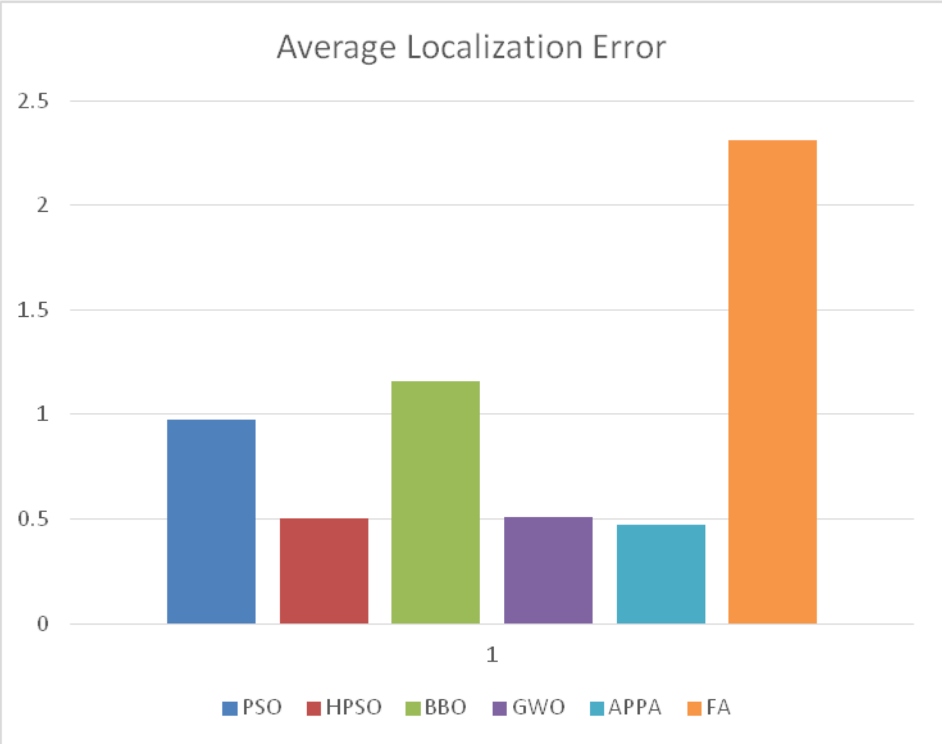


Figure 4.14: Comparison of average localization error for all the six algorithms

The performances of all algorithms have been compared with the proposed scheme in dynamic scenarios. It has been analyzed from the results given in Table 4.2 that the Average Localization error is coming out to be the minimum for all the various movements when we are using APPA Algorithm. This has basically been achieved due to the Exploitation and Exploration properties of APPA. Exploitation means searching near to optimum solutions and Exploration means coverage of search space. Similarly, Table 4.3 signifies the error values for localizing 21 nodes by all the approaches, including the proposed one.

Table 4.2: Comparison of meta-heuristic algorithms

Algorithms	Movements Number	Max Localization error	Min Localization error	Average error	Number of located targets
PSO	1	3.9358	0.0554	0.9958	80
	2	5.3379	0.0831	0.9839	80
	3	5.0108	0.0800	0.9267	80
	4	5.1655	0.0367	0.9757	80
	5	5.1325	0.0812	0.9612	80
HPSO	1	3.1204	0.1044	0.6742	80
	2	5.0134	0.0647	0.4876	80
	3	4.8279	0.0976	0.4032	80
	4	5.2376	0.0230	0.5546	80
	5	5.2134	0.0316	0.5324	80
BBO	1	5.8904	0.1822	1.1892	80
	2	5.3500	0.3318	1.2560	80
	3	5.5989	0.1822	1.1585	80
	4	5.6348	0.1528	1.2818	80
	5	5.9014	0.1911	1.1916	80
GWO	1	3.1101	0.0944	0.6442	80
	2	4.9834	0.0547	0.4776	80
	3	4.8134	0.0876	0.3932	80
	4	4.7976	0.0430	0.4946	80
	5	4.9776	0.0513	0.4713	80
FA	1	6.1101	0.1922	2.2234	80
	2	6.3120	0.3412	2.3124	80
	3	6.6990	0.1923	2.4651	80
	4	6.8912	0.1627	2.5123	80
	5	6.9036	0.2010	2.2013	80
	1	3.1101	0.0964	0.6415	80
APPA	2	4.3983	0.0437	0.4732	80
	3	4.8032	0.0721	0.3841	80
	4	4.7679	0.0412	0.4471	80
	5	4.3108	0.0403	0. 4312	80

4.5 TUNICATE SWARM ALGORITHM NAKED MOLE-RAT ALGORITHM

The TSNMRA takes the fundamental framework of NMRA and adds all of TSA's mathematical equations to the worker phase, keeping the breeder phase untouched. Here, breeder phase is meant for exploitation and the worker phase is for exploration, combining the two algorithms in their respective phases should result in a hybrid TSNMRA with proper exploration and exploitation. For localization, the proposed approach uses just one anchor node; the complicated hardware required to obtain the distance between both the anchor and target nodes is not necessary. Merely RSS data is enough to locate the location of the target nodes. The direction from which the distances between two nodes, one known and the other unknown, may be predicted is given by this information.

TSA and NMRA lower the localization error by optimizing their edge weights. Because just a single node has been employed for localization and the rest of the nodes are virtual, the suggested technique is anticipated to save energy.

Table 4.4 presents various optimization techniques used to localize the moving target nodes in the sensing field like PSO, HPSO, BBO, GWO, FA, APPA and TSNMRA for five movements corresponding to average localization error.

Table 4.3: Comparison of proposed algorithm based on localization error with existing optimization techniques

Algorithms	Movements Number	Max Localization error(m)	Min Localization error(m)	Average error(m)	Number of located targets
PSO	1	3.9358	0.0554	0.9958	80
	2	5.3379	0.0831	0.9839	80
	3	5.0108	0.08	0.9267	80
	4	5.1655	0.0367	0.9757	80
	5	5.1325	0.0812	0.9612	80
HPSO	1	3.1204	0.1044	0.6742	80
	2	5.0134	0.0647	0.4876	80
	3	4.8279	0.0976	0.4032	80
	4	5.2376	0.023	0.5546	80

	5	5.2134	0.0316	0.5324	80
BBO	1	5.8904	0.1822	1.1892	80
	2	5.35	0.3318	1.256	80
	3	5.5989	0.1822	1.1585	80
	4	5.6348	0.1528	1.2818	80
	5	5.9014	0.1911	1.1916	80
GWO	1	3.1101	0.0944	0.6442	80
	2	4.9834	0.0547	0.4776	80
	3	4.8134	0.0876	0.3932	80
	4	4.7976	0.043	0.4946	80
	5	4.9776	0.0513	0.4713	80
FA	1	6.1101	0.1922	2.2234	80
	2	6.312	0.3412	2.3124	80
	3	6.699	0.1923	2.4651	80
	4	6.8912	0.1627	2.5123	80
	5	6.9036	0.201	2.2013	80
APPA	1	3.1101	0.0964	0.6415	80
	2	4.3983	0.0437	0.4732	80
	3	4.8032	0.0721	0.3841	80
	4	4.7679	0.0412	0.4471	80
	5	4.3108	0.0403	0. 4312	80
TSNMRA	1	2.9902	0.0754	0.5516	80
	2	4.2552	0.0395	0.4328	80
	3	4.2005	0.0698	0.3526	80
	4	4.2548	0.0386	0.4032	80
	5	4.1108	0.0375	0.412	80

The representation of the five movements pertaining to average localization error corresponding to optimization methods namely PSO, HPSO, BBO, GWO, FA, APPA and TSNMRA has been depicted 4.15 to 4.19.

It has been inferred from the figure 4.14 that FA is having the highest localization error corresponding to movement 1 in contrast to other approaches. Also TSNMRA is 9 % more effective than APPA and APPA is almost working in a similar manner like the GWO.

Movement 1

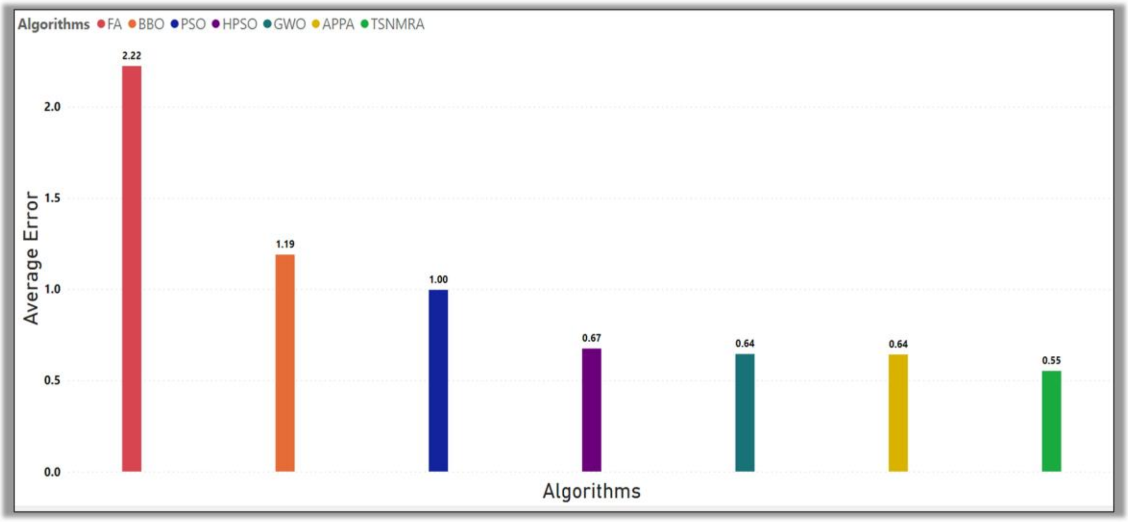


Figure 4.15: Localization error based comparison under first movement for 3D range based localization

Movement 2

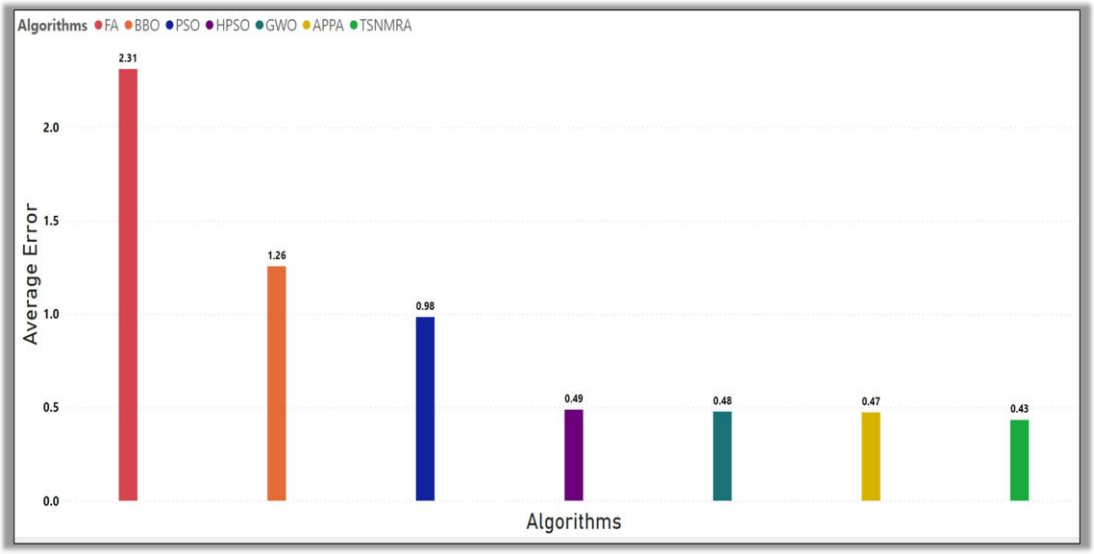


Figure 4.16: Localization error based comparison under second movement for 3D range based localization

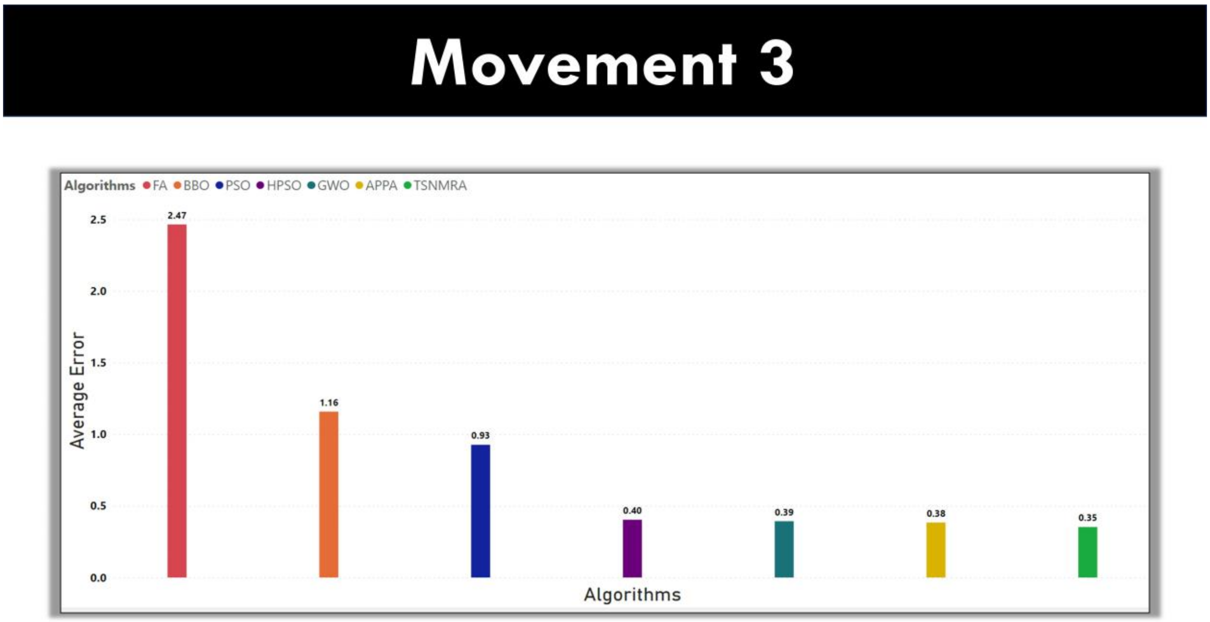


Figure 4.17: Localization error based comparison under third movement for 3D range based localization

Similar kinds of results are being inferred from the other results under various movements as depicted in figure 4.16 to 4.19. Here TSNMRA and APPA perform almost in the similar fashion

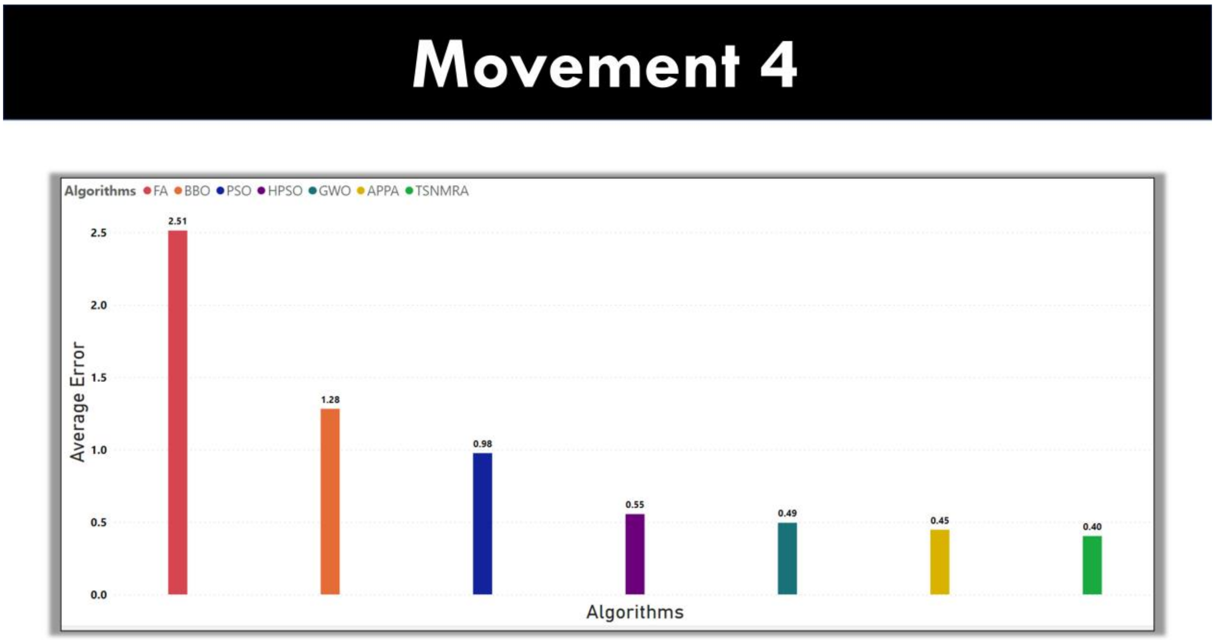


Figure 4.18: Localization error based comparison under fourth movement for 3D range based localization

Movement 5

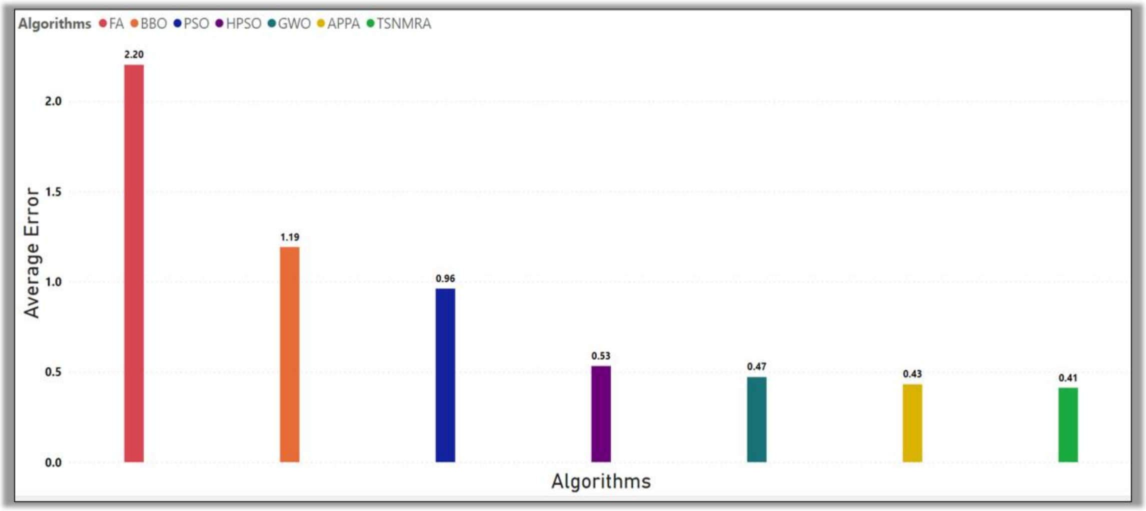


Figure 4.19: Localization error based comparison under fifth movement for 3D range based localization

From above all the results depicting the node five movements it is being clearly inferred that localization error of TSNMRA is minimal one for all the node movements corresponding to all other counter approaches. Similarly APPA outperforms other techniques such as PSO, HPSO, BBO, GWO and FA and thus is efficient one.

4.6 CONCLUSION AND FUTURE SCOPE

The single anchor node method has been used to obtain 3D positions of unknown nodes with a range-based technique using a meta-heuristic algorithm called APPA in this chapter. The idea of an anchor and virtual anchor node forms an umbrella projection for finding all unknown nodes. When the mobile nodes come in the projection of the known node, then with the help of anchor as well as virtual anchors, the position of unknown nodes is found. A variety of applications exists where sensor node location is critical, including logistics, underwater scenarios, and localization of occurring events in remote and hilly regions. The performance of the APPA algorithm in order to find out the exact location of the nodes is found to be a lot better than its competitive algorithms. It has been proved with the help of the results that using

APPA, accurate locations are being found as compared to other algorithms, and convergence characteristics are also faster. In the future, with the help of the hybridization of a few optimized algorithms, more accuracy could be achieved.

CHAPTER -5

LOCALIZING MOBILE NODES IN RANGE FREE 3D HOMOGENEOUS WSN USING METAHEURISTIC ALGORITHM

The TSNMRA approach targeting anisotropic WSNs has been suggested in this chapter as a range-free 3D node localization method using TSA and NMRA algorithms. For localization, the proposed approach uses just one anchor node; the complicated hardware required to obtain the distance between both the anchor and target nodes is not necessary. Merely RSS data is enough to locate the location of the target nodes. The direction from which the distances between two nodes, one known and the other unknown, may be predicted is given by this information. Additionally, the weights of the edges among each target node and its neighbors are employed, and these weights are represented using the Fuzzy Logic System (FLS). TSA and NMRA lower the localization error by optimizing their edge weights. Because just a single node has been employed for localization and the rest of the nodes are virtual, the suggested technique is anticipated to save energy.

5.1 FUZZY LOGIC SYSTEMS

Real estimates of variables in fuzzy logic could be any number between 0 and 1, which is multiple-valued reasoning. In 1965, Lotfi Zadeh proposed fuzzy set theory and coined the phrase "fuzzy logic." To cope with the notion of half-truth, where actual worth may exist somewhere between the two extremes of truth and lies, Fuzzy logic has been and is still being used by many academics in fields ranging from theory to AI. The resilience of a system may be improved by using fuzzy logic. The basic structure of fuzzy logic is made up of the exponential function of the input, the fuzzifier, the inference engine, the defuzzification, and the output scale parameter, as shown in figure 5.1.

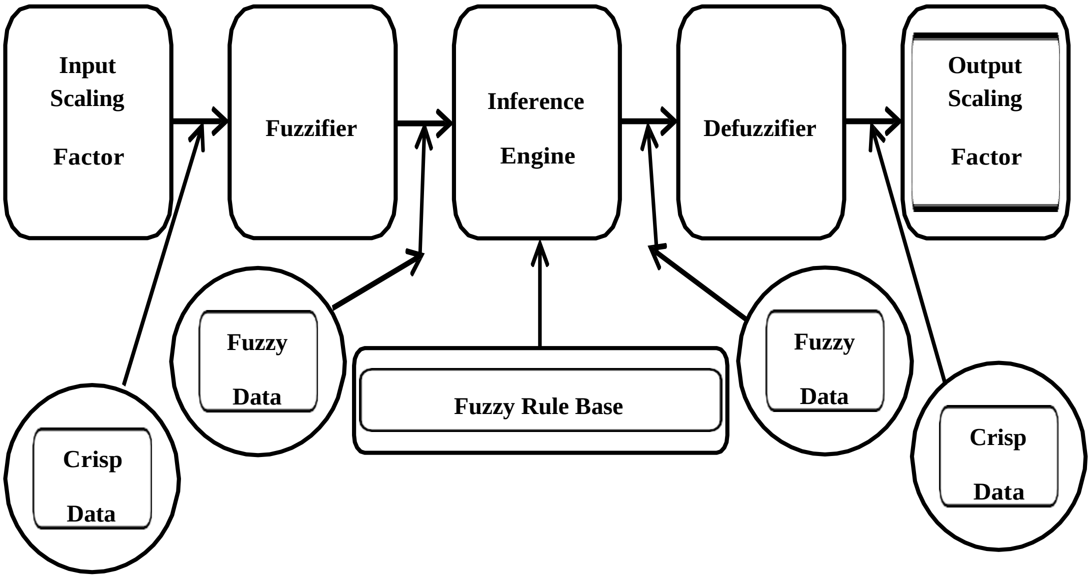


Figure 5.1: Working of the FLS through the components

- **Input/Output Scaling Factor:** A nonlinear matching of the input data set to the scalar output data is the simplest definition. The input scaling factor in FLS is used for transformation between crisp input data and the universe of discourses of the fuzzy input variables, and the output scaling factor is used to tune the output gain of the FLS.

- **Fuzzifier:** At this point, the clear input data is mixed. Using a collection of fuzzy linguistic parameters, linguistic concepts, and Fuzzy membership, this translation is carried out.

- **Inference Engine:** Decision-making is the core function of the inference engine. The output of the inference engine is always fuzzy irrespective of its input, i.e., whatever is the input (fuzzy or crisp) of the inference engine, the output is always fuzzy. Rule base, database, decision-making unit, and fuzzification interface unit are the functional blocks of a fuzzy inference system.

- **Fuzzy Rules:** This system uses a basic if-then rule with a criterion and a resolution to manage an output variable.

- **Defuzzifier:** A fuzzy dataset is defuzzified in this block. This defuzzification is done by using membership functions and crisp output is taken from this block.

The structures of rule base can be given by Equation (5.1)

$$R_i \;:\; if\; x_1 \; is\; A_{i1} \; and\; x_2 \; is\; A_{i2} \; and\; .....\; x_n \; is\; A_{in} \; then\; y_i \; is\; W_i \tag{5.1}$$

Here, R_i signifies i^{th} rule and x_j is the j^{th} intake variable of FLS. y_i signifies the i^{th} output variable while n is the number of input variables; A_{ij} represents the membership functions for the input while W_i signifies the functions for output. In this work, Mamdani implication, has been used for an input.

5.2 HYBRID TSNMRA APPROACH

Tunicate Swarm Algorithm (TSA) [188] and Naked Mole-Rat Algorithm (NMRA) [189] are two of the most recent advances in the field of swarm intelligence-based nature-inspired algorithms. Despite the fact that both TSA and NMRA are newer versions, they have been found to outperform other algorithms such as GWO, PSO, Gravitational Search Algorithm (GSA) [190], and others, as reported in the literature. The development of TSA is inspired by tunicates jet propulsion and swarming behavior when navigating and foraging, while the mating behavior of semi-arid mole rats is used to develop the NMRA. Both of these algorithms have one thing in common: they tackle the problem by using basic foraging patterns and interactions between different species. Let's go over the fundamentals of each of these algorithms one by one before discussing the hybrid approach.

TSA is based on the ability of tunicates to find the best food resources (optimal answer) in the water. However, the tunicate behaviors of jet propulsion and SI are utilized to choose the optimal source of food, i.e., the global optimum, in the defined search area. Tunicates must avoid conflicts among search agents, migrate toward the top search agent's location, and remain close to the best one in order to represent jet propulsion behavior. Search agent's placements will be regularly updated by SI activity, which is designed to identify the best possible answer. These two behaviors collectively estimate the algorithm's exploration and exploitation capabilities and found that parameters used for avoidance of conflicts among search candidates are varied for a better exploration phase. So, from the original TSA, it may be observed that the algorithm is potentially useful for exploratory operations, but much work needs to be done to improve its exploitation properties.

NMRA method is another contribution to the swarm intelligence-based algorithm and has been proven to produce more trustworthy and more efficient outcomes in comparison with other potential algorithms given in the literature. To provide a feasible solution to the problem under discussion, the algorithm employs the principles of worker and breeder naked mole-rats mating habits with the queen. Here, simpler concepts are used, and the likelihood of a breeder transitioning to a worker phase, and vice versa, is very high. It's critical that a potential male who will mate with the queen be present while moving breeders to workers or workers to breeders. This continual search for the best rat and hence a viable solution aids the NMRA in running a more efficient exploitation operation. The worker phase has a lot to give, and the global solution of the problem under test is found using two randomly picked solutions from the search space. The search space is governed by a simple scaling factor in this case, resulting in the algorithm becoming stuck in some optima or a bad exploration operation in general. Naked mole rats have bloody skirmishes called as mole rat wars which normally breaks whenever any intruder is inspected in the colony. Aside from that, the NMRA is quite easy to build and has excellent convergence features. However, the algorithm is likely to become trapped in some local optima as a result of the inadequate exploration operation.

From the foregoing description of TSA and NMRA, it is clear that both algorithms are efficient but have inherent flaws in terms of TSA's exploitation and NMRA's exploration. Thus, these algorithms exhibit premature convergence, which results in a stagnation of locally optimal solutions. As a result, we can conclude that improvements are required to increase the performance of these algorithms and proposed hybrid TSNMRA which is based on the exploration features of TSA and exploitation patterns of NMRA. Self-adaptive qualities have also been added to TSNMRA, in addition to exploration and exploitation properties, to make it a viable fit for addressing complicated real-world optimization issues. The TSNMRA takes the fundamental framework of NMRA and adds all of TSA's mathematical equations to the worker phase, keeping the breeder phase untouched. Here, breeder phase is meant for exploitation and the worker phase is for exploration, combining the two algorithms in their respective phases should result in a hybrid TSNMRA with proper exploration and exploitation. Aside from the TSA/NMRA fusion, adaption of NMRA's mating factor (λ) is done with simulated annealing (sa) mutation operato so that algorithm's parameter become self-adaptive. The inclusion of self-adaptive features makes the algorithm self-sufficient, requiring no user-based adjustment for evaluation of the problem under discussion. The hybrid TSNMRA broadly classified among 3 stages (Initialization, Worker and Breeder) and discussed as:

Initialization phase: The first phase of TSNMRA begins with initialization of mole-rats' population *(P)* randomly within a specified search range, and implemented by equation as:

$$P_{x,y} = P_{min,y} + rand(0,1) \times \left(P_{min,y} - P_{max,y}\right) \tag{5.2}$$

where $x = [1,2,3, \ldots. P], y = [1,2,3, \ldots. dim]$, $P_{x,y}$ defines the new rat solution generated for y^{th} dimension, $P_{min,y}$ and $P_{max,y}$ corresponds to search space lower and upper boundary respectively. The parameter (dim) reflects the problem's dimension taken into consideration.

Worker phase: During the worker phase, two randomly selected solutions from the search pool contribute significantly to discovering a solution close to the optimal solution in classical NMRA. It is taken as the exploration phase of the algorithm and found that less efficient, so the additional effort is needed to enhance its functioning properties. Thus, NMRA's worker phase working capability is improved by adding the characteristics of TSA.

About half of the iteration were indeed a success, mathematical equations of TSA's jet propulsion and swarm behaviour are incorporated to NMRA's worker phase. The jet propulsion behaviour is implemented by taking the three conditions under evaluation such as conflicts avoidance between search candidates, approaching of search candidate towards best position and preserves its position near to best candidate. The vector $\vec{\beta}$ is used for avoiding conflicts among search agents and is given as:

$$\vec{\beta} = \frac{\vec{g}}{\vec{m}} \tag{5.3}$$

$$\vec{g} = d + d_3 - \vec{f} \tag{5.4}$$

$$\vec{f} = 2.d_1 \tag{5.5}$$

where $\vec{g}$ signifies gravity force, $\vec{f}$ signifies water flow in sea, 3 parameters (d_1, d_2, d_3) are allocated in random fashion between 0 and 1, $\vec{m}$ concerns with forces between search candidates and incurred as:

$$\vec{m} = [p_{min} + d_1.p_{max} - p_{min}] \tag{5.6}$$

where p_{max} and p_{min} signifies search candidates speed of interaction and its value is considered as 4 and 1 respectively.

After avoiding conflicts, tunicates begin to move towards the best candidate's position, which is computed as follows:

$$\vec{d} = |\vec{f_s} - r.\vec{p}(t)| \tag{5.7}$$

where $\vec{d}$ corresponds to distance among food's position and search agent, t is value of present iteration, r is divided in range [0,1] randomly, $\vec{f_s}$ presents food's optimal location and $\vec{p}$ signifies search candidate's position for present iteration.

In the last condition of jet propulsion behaviour, search candidates must keep their location near the best search candidates (location of food) and be characterized as follows:

$$\vec{p}(t) = \begin{cases} \vec{f_s} + \vec{\beta}.\vec{d}, & r \geq 0.5 \\ \vec{f_s} - \vec{\beta}.\vec{d}, & r < 0.5 \end{cases} \tag{5.8}$$

here $\vec{p}(t)$ performs position updation of search agents with respect to location of food $\vec{f_s}$.

The second behaviour exhibits by tunicates are swarm intelligent and describe as:

$$\vec{p}(t+1) = \frac{\vec{p}(t)+\vec{p}(t+1)}{2+c_1} \tag{5.9}$$

here $\vec{p}(t)$ and $\vec{p}(t+1)$ treated as two best solutions and these solutions are kept for updating other candidate's result in accordance with location of best candidate.

For the second half of iterations, worker phase is implemented with general equation used in original NMRA and calculated as:

$$ws_p(t+1) = ws_p(t) + \lambda\big(ws_c(t) - ws_d(t)\big) \tag{5.10}$$

where $ws_p(t)$ defines worker's solution for t^{th} iteration, $ws_p(t+1)$ is newly generated solution, λ represents rats' mating behaviour, $ws_c(t)$ & $ws_d(t)$ are two results that are randomly chosen from pool of worker mole-rats.

Breeder phase This phase of hybrid TSNMRA is considered as exploitation phase and performed by a limited number of breeders rats for mating with the queen (optimal global solution). The main reason for using exploitation in the global search phase is that it looks for a solution that is close to the current best solution and is predicted to produce a global solution near the end of iterations. The breeding phase for the hybrid TSNMRA is identical to that of classical NMRA, and no changes have been made to this phase. The equation for updating the breeder rat solution is as follows:

$$bs_p(t+1) = (1-\lambda)bs_p(t) + \lambda\left(P_{best} - bs_p(t)\right) \tag{5.11}$$

where bs_p represents the breeder rats' solution in the t^{th} iteration, λ regulates the frequency of mating and $bs_p(t+1)$ represents the new solution developed in the next cycle. The breeding probability *(bp)* is used to update the fitness of these breeders in consideration with the beginning best solution P_{best}.

Apart from TSA and NMRA hybridization in TSNMRA, it also includes parameter adaptation of NMRA’s mating factor (λ) with simulated annealing (sa) mutation operator and mating component doesn't need a random or constant quantity to be assigned. The convergence speed of the optimization method is improved by the mutation operator, which is defined as:

$$\alpha_{sa} = \alpha_{min} + (\alpha_{max} - \alpha_{min}) \times \beta^{(k-1)} \tag{5.12}$$

where α_{min}, α_{max} and k distributed randomly in the range [0,1] and β is fixed to 0.95.

A greedy selection strategy is used to narrow the field of potential candidates for TSNMA's final step of evaluation. There should be no need to keep a pre-computed answer if a freshly generated one has a superior fitness score than that of that earlier produced one.

5.3 TSNMRA INTEGRATION WITH FLS

Many present methods of localization rely on a perfect spectrum rather than taking Degree of Irregularity (DOI) into account at all. In reality, however, this is not achievable. Radio-irregularity is thus an important consideration when examining a pattern in the actual world. In wireless networks, it is impossible to ignore the issue of radio irregularity. Various radio anomalies are also taken into account in our methodology. The radio trend will become unpredictable as a result of the signal being sent with varying RF strengths and path losses. A Radio Irregularity Model (RIM) is taken into account to determine the propagation medium's anisotropic features [104]. A DOI parameter in figure 5.2 calculates the irregularity in the radiation pattern.

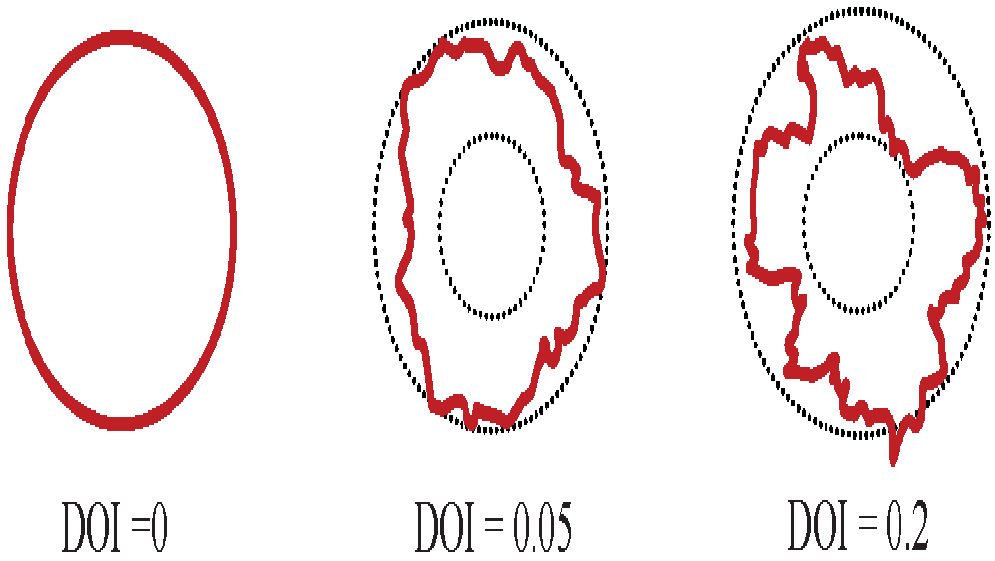


Figure 5.2: DOI representation for irregular radio patterns for different values

5.3.1 Formulation of Problem

Using anchor and target nodes in a three-layer framework, sensors may be located in a 3D environment. Because it is movable, the anchor node changes location at various times. An anchor node's range encompasses the whole area, which is organized into grids. The whole area is believed to be covered by the motion of an anchor node. Most unknown nodes receive beacon details from an anchor node and use them to calculate their distance from the anchor node. Distance may be calculated using just the RSSI data collected as part of a range-free localization method.

In order to calculate the target node's position, a new idea of selecting virtually distributed anchors is added as soon as it arrives inside the scope of the anchor node. Each anchor node calculates the Euclidean distance for each move. To be deemed localizable, a target node must be closer to the anchor node's reach than the Euclidean distance. The antenna node is broadcast in tandem with six 'virtually assumed' anchors. To determine the distance between a target node and an anchor node using the range-free approach, all that is needed is RSS data. The route of a signal may alter throughout the process of acquiring RSS information owing to environmental obstructions. Path loss, lognormal fading, and Rayleigh fading are the most often utilized propagation methods in WSN. Over a shorter distance, the RSS signal fluctuates. In our work, we take into account all environmental factors that might affect efficiency.

5.3.2 TSNMRA with Fuzzy Logic Based Localization

All of the target nodes in a 3D sensing region are thought of as being located by a singular anchor node in this work. The two levels of the sensing field are randomly distributed with target nodes. This sensor field has a top-to-bottom structure with anchor and target nodes arranged in a random fashion. Nodes in the moving target network use the beacon signals sent by the anchor node to assist them in determining their location. The anchor node's RSS data may be calculated and collected by listening to the beacon for a certain amount of time once the target nodes are within its range. A moving target node's Euclidean distance from an anchor node is determined.

An umbrella projection is then used to locate the target node after computing the Euclidian distance, as seen in figure 5.3. Due to radio irregularity and diversity, the transmission distances are not similar in this work, and as a result, radio propagation is indeed not exactly spherical. Through GPS or any other method, the location of the anchor node may be determined.

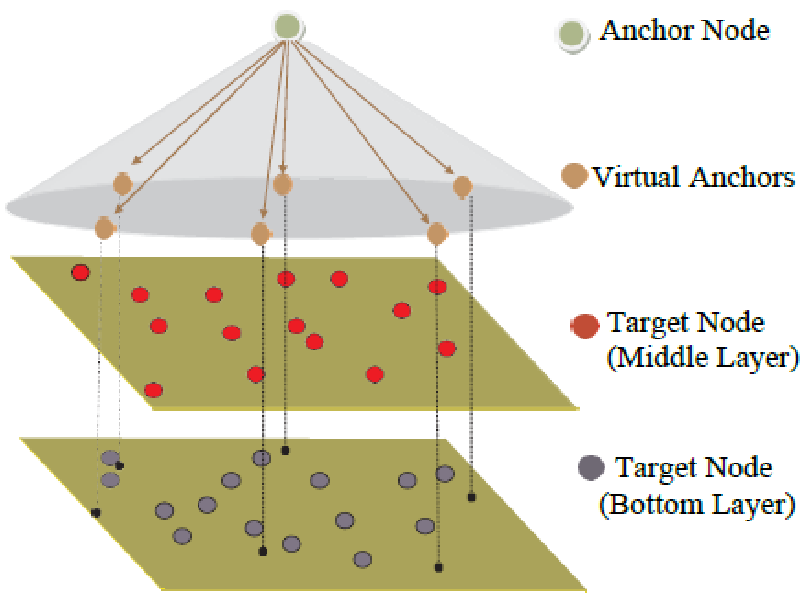


Figure 5.3: Localization process based on 3D

3D dynamic node localization is carried out in the manner described below.

1. The middle and bottom layers of the 3D sensing area have a random distribution of mobile target nodes (*M*), whereas the top layer has a single anchor node.

2. Anchor and target nodes are separated by the RIM and heterogeneity properties by using equation 5.13.

$$d_i\hat{} = d_i-(D_p+F) \tag{5.13}$$

in which d_i signifies actual distance, D_p represents DOI adjusted path loss and F signifies fading.

3. Collect the IDs and positions of anchor and virtual anchor nodes and compute their RSS through equation 5.14

$$RSS_{ij} = \frac{\upsilon}{d_{ij}^{\alpha}} \tag{5.14}$$

Where RSS_{ij} signifies RSS among i_{th} target and j_{th} anchor node. In our scenario, the value of j is equal to 1. υ is the constant and α is the attenuation exponent and d_{ij} is the distance among i_{th} target and j_{th} anchor node.

4. Check whether the count of adjacent anchor and virtual anchor node ≥ 4

5. Moving target nodes are connected to their anchor and virtual anchors by edge weights. FLS was used to simulate these edge weights.

6. TSA and NMRA are used to build the weights and fuzzy sets of the rule base, which are then used to construct an adequate and less repetitive rule base for precise target node positions.

7. Determine the location of target nodes by utilizing the edge weights among each surrounding anchor and virtual anchor node by equation 5.15.

$$(x_t, y_t, z_t) = \frac{(w_1x_1)+\cdots+(w_kx_k)}{\sum_{i=1}^{k} w_i}, \frac{(w_1y_1)+\cdots+(w_ky_k)}{\sum_{i=1}^{k} w_i}, \frac{(w_1z_1)+\cdots+(w_kz_k)}{\sum_{i=1}^{k} w_i} \tag{5.15}$$

5.3.3 Fuzzy Modelling Through Edge Weights

Basically, RSS is the measured voltage by the receiver from the anchor node. The distance between the anchor and the destination node is given as an indication. FLS with Mamdani inference has been utilized in this work to simulate the connection between the weight of an anchor node and its RSS in order to solve RSS uncertainty and nonlinearity among RSS and distance estimates.

The variable in Figure 5.4 shows how RSS is plotted into five parameters using S, triangular, and Z-type membership functions. Put either of these membership group values into the rule set to finish it off, i.e., *Wi* is either very low, low, medium, high, and very high. A degree of importance is applied to each rule, given by equation (5.16). Where $\mu(x)$ is the membership grade of the input and $\mu(y)$ is the membership grade of the output. Through Equation 5.16, redundant rules from the rules are eliminated.

$$Degree\ of\ importance = \mu(x) \times \mu(y) \tag{5.16}$$

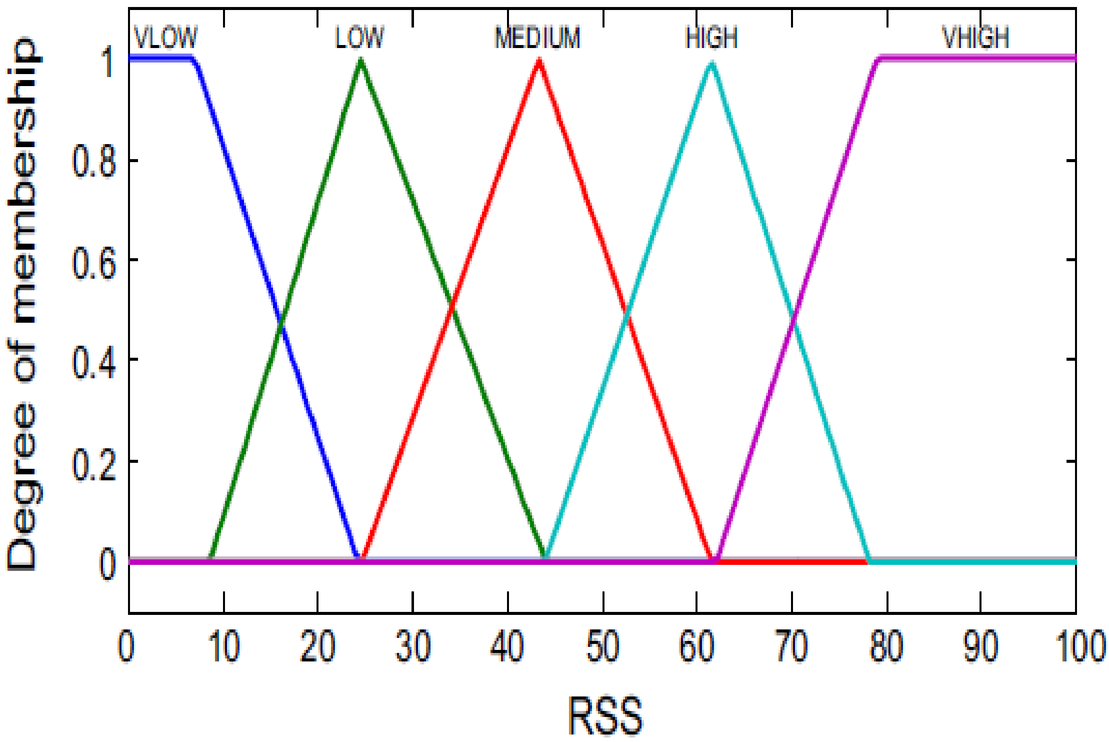


Figure 5.4: Initial RSS fuzzy membership functions

5.4 IMPLEMENTATION AND ANALYSIS

In this chapter, the novel idea of 3D range free node localization has been proposed with umbrella-based projection. TSA and NMRA-based CI techniques are employed in range-free scenarios to get the 3D location information of target nodes termed TSNMRA. Hierarchical node heterogeneity and a very chaotic cubic architecture are explored in this chapter. 3 D simulations have been carried out on a 10x 10x10m3 area, and the anchor node is placed at [5 5 5], i.e., the top layer. Target nodes are placed on the second and third layers, which are moving in a random pattern at random intervals. Using umbrella projection, six virtual anchor nodes in the nearby region are projected, and three virtual anchor nodes (next to the anchor and moving target) are picked to identify the 3D location. The edge weights among nearby anchor nodes and each moving target node are also used. FLS was used to simulate these weights in the final product. The optimization of these edge weights is done by TSA and NMRA to reduce the localization error. The strategic settings for both techniques are given by Table 5.1.

Table 5.1: Parameters taken for TSA and NMRA

TSA		**NMRA**	
Parameter	**Value**	**Parameter**	**Value**
Population size	20	Population size	20
Maximum count of iterations	100	Maximum count of iterations	100
Inertia Weight (ω)	0.729	Probability of Mutation of Particle Weight	0.05
Cognitive, Social and Neighborhood Learning Parameters	1.429	Maximum Rate of Emigration	1
Random Value Interval	0 to 1	Maximum Rate of Immigration	1
Noise Variance	0.02	Noise Variance	0.02
DOI	0.01	DOI	0.01

The simulation is done for a single trial having 100 iterations. The simulation is done for single trial because there is a requirement of less convergence rate in dynamic scenarios. Figures 5.5 and 5.6 give the optimization results of the edge weights.

Spatial results of proposed localizing techniques using TSNMRA algorithm has given by figures 5.7.

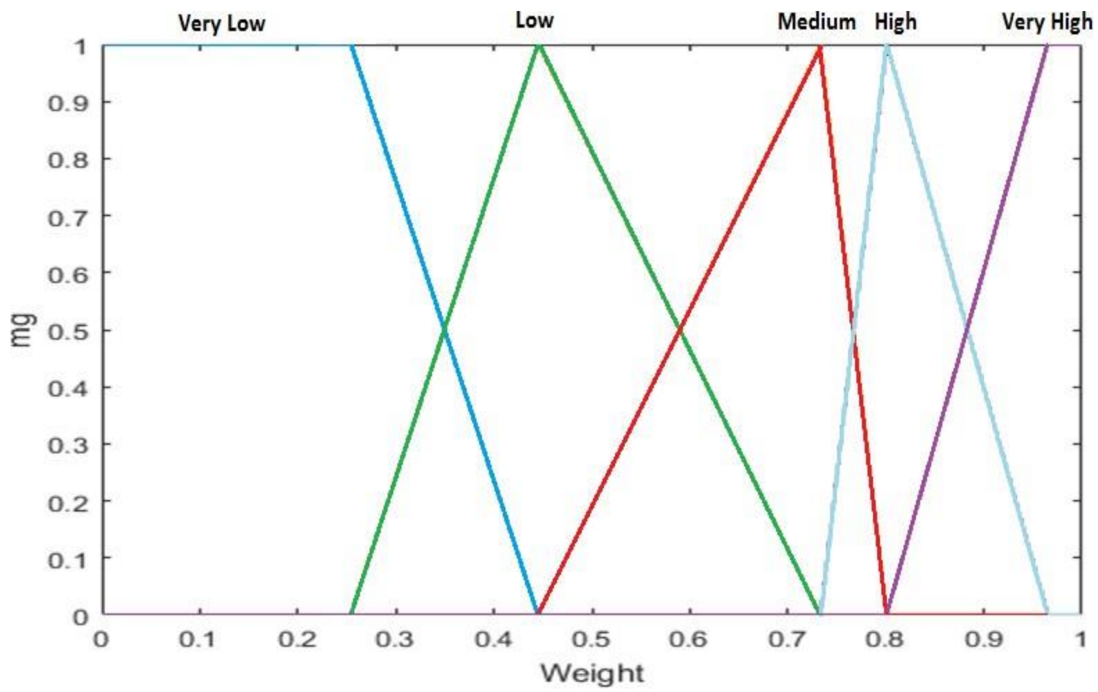


Figure 5.5: TSA optimized fuzzy membership edge weights

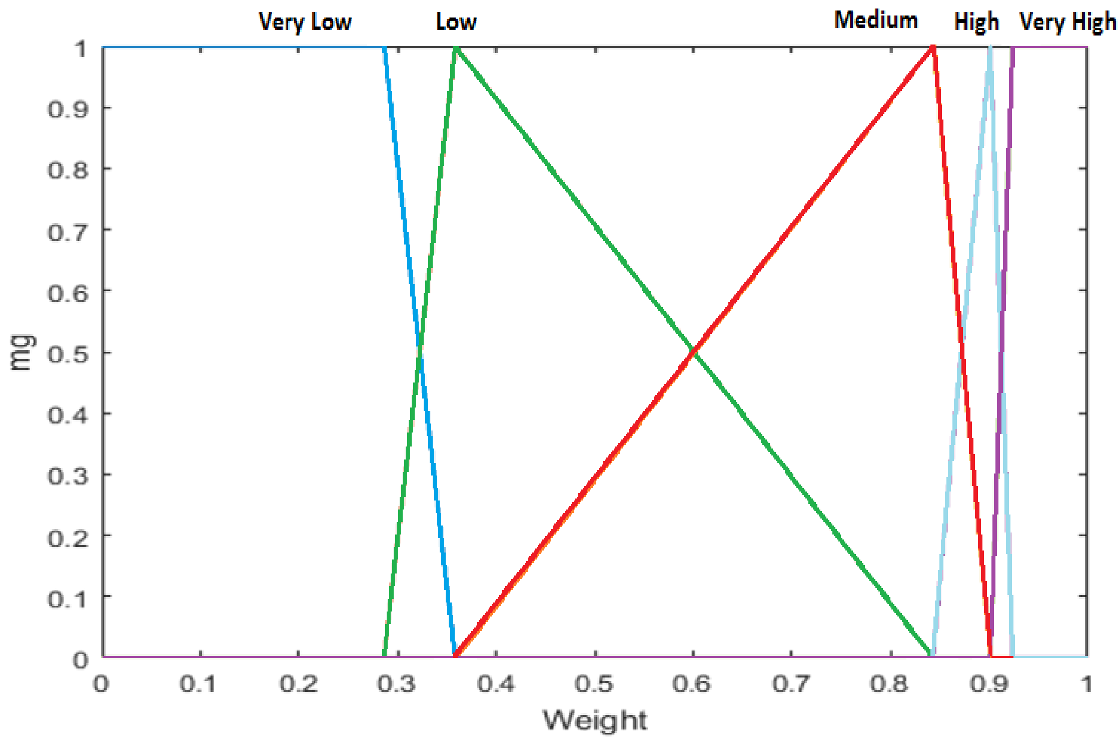


Figure 5.6: NMRA optimized fuzzy membership edge weights

It is in this chapter that the suggested algorithm TSNMRA is evaluated to various meta-heuristics that have been established. Tables 5.2 show the simulation findings. It gives the results of the proposed algorithms for dynamic scenarios (mobile target nodes). Maximum Localization Error, Minimum Localization Error and Average Localization Error (ALE) are considered as performance indices of the proposed techniques.

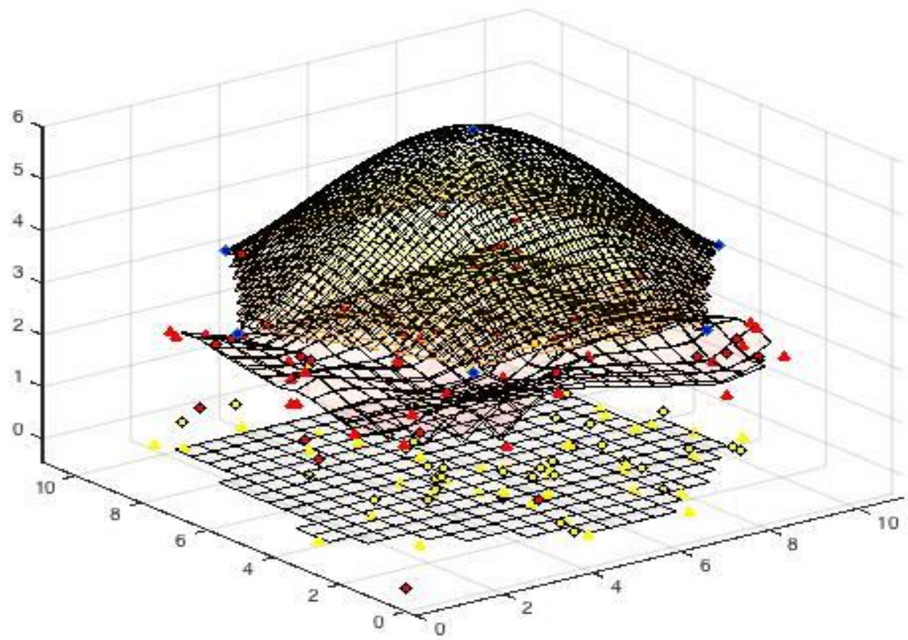


Figure 5.7: TSNMRA based 3D node localization

Table 5.2: Comparative analysis of TSNMRA with other met heuristic approaches

Algorithms	Movements Number	Max Localization error(m)	Min Localization error(m)	ALE(m)	Number of located targets
PSO	1	3.9358	0.0554	0.9958	80
	2	5.3379	0.0831	0.9839	80
	3	5.0108	0.08	0.9267	80
	4	5.1655	0.0367	0.9757	80
	5	5.1325	0.0812	0.9612	80
	1	3.1204	0.1044	0.6742	80

HPSO	2	5.0134	0.0647	0.4876	80
	3	4.8279	0.0976	0.4032	80
	4	5.2376	0.023	0.5546	80
	5	5.2134	0.0316	0.5324	80
BBO	1	5.8904	0.1822	1.1892	80
	2	5.35	0.3318	1.256	80
	3	5.5989	0.1822	1.1585	80
	4	5.6348	0.1528	1.2818	80
	5	5.9014	0.1911	1.1916	80
GWO	1	3.1101	0.0944	0.6442	80
	2	4.9834	0.0547	0.4776	80
	3	4.8134	0.0876	0.3932	80
	4	4.7976	0.043	0.4946	80
	5	4.9776	0.0513	0.4713	80
FA	1	6.1101	0.1922	2.2234	80
	2	6.312	0.3412	2.3124	80
	3	6.699	0.1923	2.4651	80
	4	6.8912	0.1627	2.5123	80
	5	6.9036	0.201	2.2013	80
APPA (Proposed)	1	3.1101	0.0964	0.6415	80
	2	4.3983	0.0437	0.4732	80
	3	4.8032	0.0721	0.3841	80
	4	4.7679	0.0412	0.4471	80
	5	4.3108	0.0403	0. 4312	80
TSNMRA (Proposed)	1	2.9902	0.0754	0.5516	80
	2	4.2552	0.0395	0.4328	80
	3	4.2005	0.0698	0.3526	80
	4	4.2548	0.0386	0.4032	80
	5	4.1108	0.0375	0.412	80

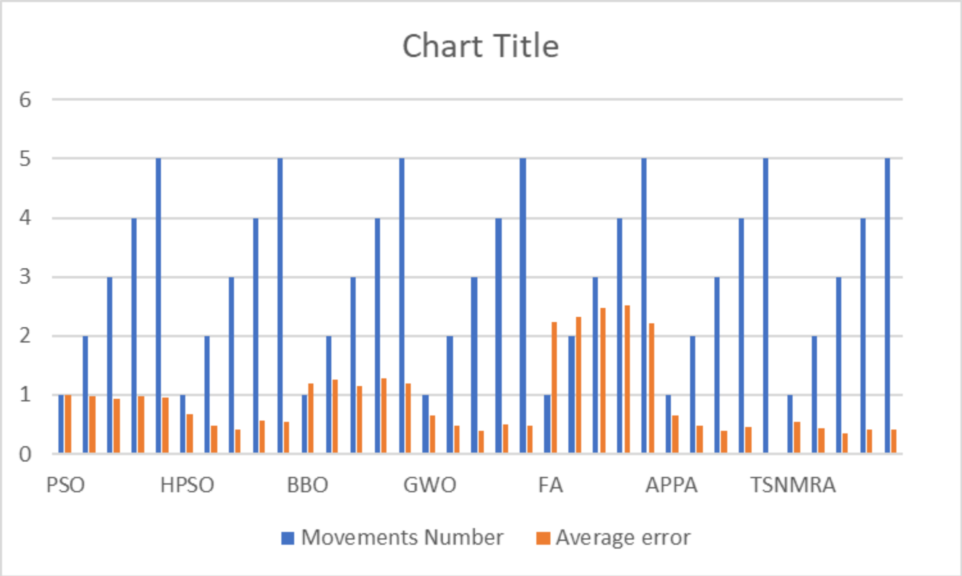


Figure 5.8: Graphical comparison of TSNMRA with other metaheuristic approaches

As indicated in Table 5.2, the algorithms we have developed are contrasted to those that exist already. In general, this table shows that the mobility-based algorithm described in our work surpasses the static methods despite the fact that mobile contexts have various hurdles. This is basically achieved due to the hybridization of TSA and NMRA which involves the Exploitation features of TSA and Exploration features of NMRA.

Table 5.3 gives the results of the proposed algorithms for dynamic scenarios (mobile target nodes). Here, ALE is considered as performance indices of the proposed technique and it is being compared with other techniques considering their range free nature.

Table 5.3: ALE analysis for range free localization methods

Algorithm Details	**Average Localization Error(m)**
Weighted Centroid	4.306
RF-HPSO	3.268
RF-BBO	3.17
RF-BFO	2.898
RF-IWO	2.767

RF-HPSO	0.869
RF-BBO	0.917
RF-APPA	0.904
RF-TSNMRA	0.785

Figure 5.8 represents the variation of ALE for the various range free approaches. It is being inferred that the RF-TSNMRA (Proposed) has the least value of ALE and thus it is effective in contrast to other methods.

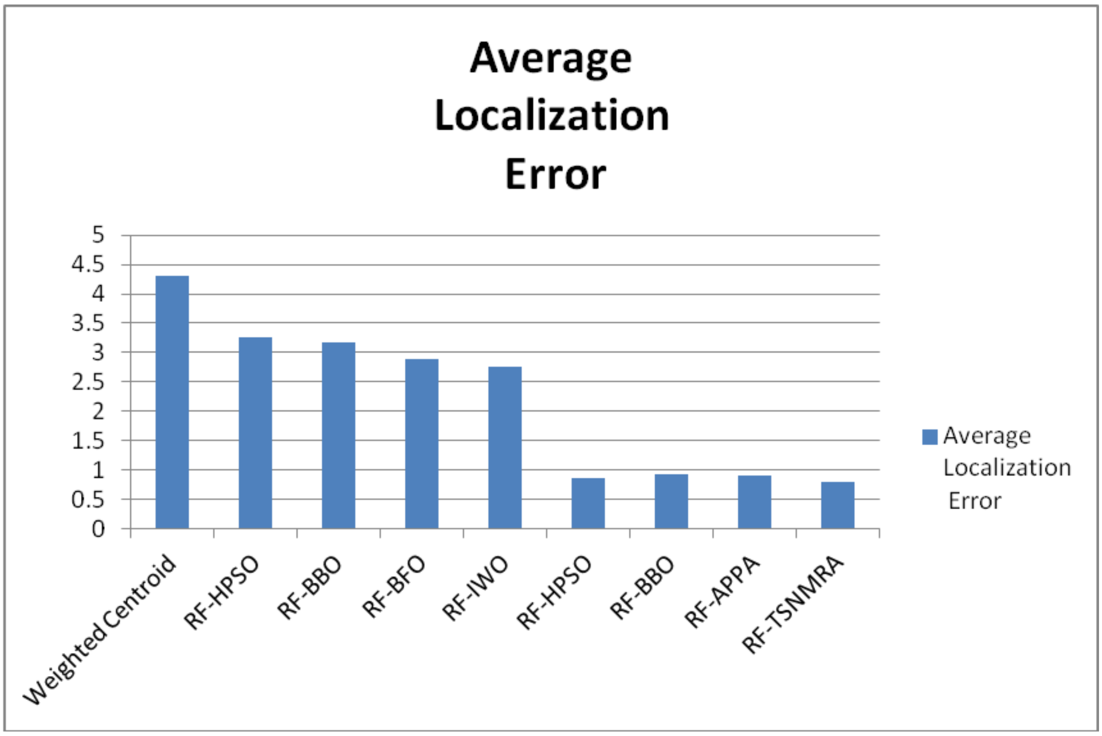


Figure 5.9: Analysis of ALE for range free approaches

As given in Table 5.4, results of localization algorithms used for static scenarios, viz. weighted centroid, RF-HPSO, RF-BBO, RF-IWO, RF-APPA and RF-BFO are compared with proposed localization technique (RF-TSRMA) used for dynamic scenarios.

Table 5.4: Comparative analysis based on static and dynamic scenarios with minimum anchor

Algorithm	Static/Dynamic	Area (m^3)	Number of Anchors (In Percentage) corresponding to Target Nodes	Maximum Localization Error(m)	Minimum Localization Error(m)	Average Localization Error(m)
Weighted Centroid	Static	10 × 10 × 5	4%	7.601	1.011	4.306
RF-HPSO	Static	10 × 10 × 5	4%	5.811	0.726	3.268
RF-BBO	Static	10 × 10 × 5	4%	5.612	0.729	3.17
RF-BFO	Static	150 × 150 × 150	4%	5.118	0.679	2.898
RF-IWO	Static	150 × 150 × 150	4%	4.902	0.632	2.767
RF-HPSO	Dynamic	10 × 10 × 5	only 1 (Single)	2.063	0.131	0.869
RF-BBO	Dynamic	10 × 10 × 5	only 1 (Single)	2.126	0.219	0.917
RF-APPA	Dynamic	10 × 10 × 10	only 1 (Single)	2.005	0.204	0.904
RF-TSNMRA	Dynamic	10 × 10 × 10	only 1 (Single)	1.985	0.19	0.785

The results with the minimum number of anchor nodes for the static scenario using various CI techniques have been considered for comparison. The proposed range-free algorithm (RF-TSRMA) considers only a single anchor node has better localization accuracy on account of less ALE, whereas localization error is very high while considering a minimum 4 % anchor node with respect to target nodes for other static scenarios.

5.5 CONCLUSION AND FUTURE WORK

In this chapter, a range-free fuzzy logic-based 3D dynamic node localization technique has been proposed using TSA and NMRA-based CI concepts for anisotropic WSNs. Target and nearby anchor node distance information can be obtained using the proposed approaches with minimal hardware. The position of the moving target node can be estimated by RSS information only. As a result of this, edge weights are employed to describe weights among target nodes and their nearby anchor and virtual anchor nodes. The optimization of these edge weights is done by TSA and NMRA to reduce the localization error. According to the simulation results, the RF-TSNMRA approach has greater localization accuracy than other methods in the literature, such as the weighted centroid method and the RF-HPSO, RF-BBO, and RF-IWO. Because mobile circumstances provide a number of unique obstacles, the mobility-based algorithm described in our work outperforms static methods. Better localization accuracy may be achieved in the future using hybrid localization, a mix of range-based and range-free techniques utilizing the CI approach.

CHAPTER -6

SUMMARY

This chapter presents a concise outline of the research work done with key findings and significant contributions. A summary of the work in this thesis with its future scope describing the areas in which further advancement of the research work can be done is presented below.

6.1 CONCLUSIONS

Chapter 1 explores the basics of WSNs with their architecture and characteristics, which make them promising for a number of applications in real life. Further, it extends to the application areas and various research challenges in WSNs. This has been followed by the basics of the WSN localization process. It also covers the major classification of localization algorithms. Motivation, main objectives, and contributions in this thesis have been discussed. The chapter concludes with the organization and outlines of the remaining chapters.

Chapter 2 provided an extensive survey related to range-free and range-based localization techniques. The reviews of the various localization techniques for static and dynamic WSNs have been done. A lot of work has been reported in the literature based on target node localization and the usage of Meta heuristic concepts for accurate localization. The literature on WSN localization describes in-depth the numerous obstacles in identifying the sensor node. This chapter has shown some of these nature-inspired approaches and their application in different WSN scenarios. Furthermore, the parameters that are relevant for evaluating the localization algorithms are emphasized.

In chapter 3, the DA Meta heuristic optimization localization technique for identifying locations of randomly arranged target nodes has been proposed. To begin, the anchor and the target node distance is calculated after the notion of VN's is proposed, with VN's being placed at certain angles in the field at a fixed distance between the anchor and the target node. Then centroid is computed, and DA is used to compute the localization error. The proposed technique can be used in a variety of applications, including logistics and military. For 3D localization, DA can also be used to determine 3D coordinates efficiently. Similarly to the DA approach, one new method based on NN has been provided. This chapter presents the NNA meta-heuristic optimization localization technique. The computations of location have been performed using two components. After calculating the distance between AN and TN, the notion of VNs is offered, with VNs positioned in the field at certain angles and a set distance among both the nodes. Afterward, the centroid is determined, and the localization error is estimated using NNA.

In chapter 4, a range-based strategy and a meta-heuristic algorithm known as APPA has been proposed. The 3D locations of unknown nodes are obtained using a single anchor node. The concept of an anchor and virtual anchor node provides a projection umbrella for locating all unknown nodes. When mobile nodes enter the projection of a known node, the location of unknown nodes is estimated using both physical and virtual anchors. Using the findings, it has been shown that APPA finds more precise locations than other algorithms and that convergence features are also quicker.

In chapter 5, the TSNMRA approach targeting anisotropic WSNs has been suggested, which is a range-free 3D node localization method using TSA and NMRA algorithms. For localization, the proposed approach uses just one anchor node; the complicated hardware required to obtain the distance between both the anchor and target nodes is not necessary. Merely RSS data is enough to locate the location of the target nodes. Additionally, the weights of the edges among each target node and its neighbors are employed, and these weights are represented using the Fuzzy Logic System (FLS). TSA and NMRA lower the localization error by optimizing their edge weights. To reduce computational complexity, FLS has been used to simulate RSS and edge weight. The simulation results revealed that the RF-TSNMRA approach has greater localization accuracy than other methods in the literature, such as the weighted centroid method and the RF-HPSO, RF-BBO, and RF-IWO. Because mobile circumstances provide a number of unique obstacles, the mobility-based algorithm (TSNMRA) outperforms static methods.

6.2 LIMITATIONS AND FUTURE WORK

Typically, a solution to a problem produces several difficulties that must be examined. This work does not deviate from this fundamental rule. In both instances, the performance of the suggested strategies for WSN localization is superior (range-based and range-free). There is, however, always room for development in every effort. The following are the future study directions pertinent to this thesis:

- The analysis and the implementation of range free localization algorithms in other deployment models apart from the regular model is being required.

- Nature inspired schemes has been utilized for range based & range free 2D/3D dynamic node localization. Some hybridization of these nature inspired algorithms may be a better solution to minimize the localization error.

- Security of the localization process in terms of the authenticity of the nodes involve in the process under the presence of various attacks can be done in future research.

- The real time implementation of the proposed approaches either using the test beds or deploying them in some scenarios likes habitat monitoring and defense side can be looked upon.

- The strategical parameters for all Algorithms were not that strict. These could be modified.

- A lot of work can be done on Energy Conservation, which was slightly challenging aspect in this research.

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