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An Efficient Approach for Localizing Sensor Nodes in 2D Wireless Sensor Networks Using Whale Optimization-Based Naked Mole Rat Algorithm

Goldendeep Kaur [1,2], Kiran Jyoti [2], Samer Shorman [3], Anas Ratib Alsoud [4] and Rohit Salgotra [5,6,7,*]

1 Department of Computer Science and Engineering, IK Gujral Punjab Technical University, Jalandhar 144603, Punjab, India; goldendeep@gndec.ac.in
2 Department of Computer Science and Engineering, Guru Nanak Dev Engineering College, Ludhiana 141006, Punjab, India; kiranjyotibains@gndec.ac.in
3 College of Arts and Science, Applied Science University, Al Eker P.O. Box 5055, Bahrain; samer.shorman@asu.edu.bh
4 Hourani Center for Applied Scientific Research, Al-Ahliyya Amman University, Amman 19328, Jordan; a.alsoud@ammanu.edu.jo
5 Faculty of Physics and Applied Computer Science, AGH University of Science and Technology, 30-059 Kraków, Poland
6 Faculty of Information Technology, Middle East University, Amman 11813, Jordan
7 Data Science Institute, University of Technology Sydney, Sydney 2007, Australia
* Correspondence: r.03dec@gmail.com or rohits@agh.edu.pl or rohit.salgotra@uts.edu.au

Abstract: Localization has emerged as an important and critical component of research in Wireless Sensor Networks (WSNs). WSN is a network of numerous sensors distributed across broad areas of the world to conduct numerous activities, including sensing the data and transferring it to various devices. Most applications, like animal tracking, object monitoring, and innumerable resources put in the interior as well as outdoor locations, need to identify the position of the occurring incident. The primary objective of localization is to identify the locality of sensor nodes installed in a network so that the location of a particular event can be traced. Different optimization approaches are observed in the work for solving the localization challenge in WSN and assigning the apt positions to undiscovered sensor nodes. This research employs the approach of localizing sensor nodes in a 2D platform utilizing an exclusive static anchor node and virtual anchors to detect dynamic target nodes by projecting these six virtual anchors hexagonally at different orientations and then optimizing the estimated target node co-ordinates employing Whale Optimization-based Naked Mole Rat Algorithm (WONMRA). Moreover, the effectiveness of a variety of optimization strategies employed for localization is compared to the WONMRA strategy concerning localization error and the number of nodes being localized, and it has been investigated that the average error in localization is 0.1999 according to WONMRA and is less than all other optimization techniques.

Keywords: WSN; optimization; localization; WONMRA

MSC: 68W50

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1. Introduction

The development of wireless technology has inspired numerous researchers to study WSNs. These networks allow for the placement of nodes that can sense, calculate, and transmit critical information to other nodes in the vicinity of the area of concern [1]. With sensor nodes placed randomly or in specified locations, WSNs can be applied to a number of tasks, including reducing air pollution, detecting forest fires, military applications, and spying [2]. WSNs offer a number of advantages: accommodating new devices at any time, avoiding the need for wiring, accessing through a centralized mirror, and flexibility to move through partitions. At the same time, WSN has its disadvantages, too, including distraction by various elements like Bluetooth. It is also easier for hackers to hack and possesses lower communication speed. There are two different types of WSNs: structured and unstructured. Lesser nodes make up a network referred to as a "structured WSN." Unstructured WSNs struggle with a number of issues, such as network upkeep and ensuring node connectivity [2]. Nodes, once installed in the remote environment, remain disregarded, thereby making their security difficult and problematic. Sensor networks include a number of traits, including compact size, lesser consumption of energy, fewer storage needs, and limited computing capability, due to which sensor networks are among the intriguing research topics. Moreover, sensor nodes are more energy-intensive and unstable but can be used often as they are less expensive.

These numerous issues in WSNs need to be addressed, including the architecture of the network, routing, finding the location of nodes, power limits, memory, and others [3–5]. Localization is a significant problem as it is crucial to know the location of the reporting incidence because without it the data will be worthless. Thousands of nodes need to locate their positions in WSN. The localization also has to deal with node failure and node self-localization [6–8]. Routing between the numerous sensor nodes and power problems are two additional WSN concerns.

The most crucial aspect of WSNs is localization, which can be employed in static as well as dynamic scenarios. Finding each sensor's exact location in 2D and 3D scenarios is the main objective [9]. The sensors deployed in large areas and having movement are more complicated to discover. Because of cost and power limits, equipping each node with GPS functionality is also impractical. In some places, localization is also performed in a dynamic context for moving sensor nodes [10–12].

The practice of assigning a location in respect of two-dimensional as well as three-dimensional sets of parameters to each node or set of nodes deployed collectively or alone in the sensor region is known as localization. There are numerous ways to allocate node positions, such as manually or by employing a Global Positional System (GPS). Manual location allocation is a complicated task, but employing the GPS in all the sensor nodes is also not a feasible option due to the increasing cost of deploying nodes in the field. To overcome this situation, some of the nodes are equipped with GPS and are referred to as anchor nodes. These anchor nodes are used as a reference to compute the location of the unknown nodes. The localization approach restricts sensor nodes in WSNs on the basis of input applied. If the WSN has anchor nodes, the position of their nodes is used as an intake.

The strategies of localization are segregated among the range-based and range-free approaches. Range-based techniques make use of the distance between the nodes based on the received strength of the signal, angle of arrival of the signal, and time of arrival of the signal, while range-free techniques make use of hop counts between the nodes with minimum infrastructure. Sensor nodes with unidentified parameters, referred to as target nodes, are located using localization algorithms. Anchor nodes may be utilized to investigate the position of all undiscovered nodes because they have inbuilt GPS capability, so their exact location is already known.

Discovering in-range anchor nodes, computing the distance as well as position, and estimating the location are three basic steps of the localization task. After estimating the distance between the anchors and the relevant target nodes, the parameter values of the target nodes are calculated. Figure 1 depicts the five different types of WSN localization techniques.

Many researchers have worked in this area, but the problem is 2–3 anchor nodes are required to compute the location of undiscovered nodes. Moreover, there is a need to improve the accuracy of localized target nodes. So, in this work, the notion of taking an exclusive anchor node along with its virtual projection in six different orientations at an angle of 60° is presented by utilizing the Whale Optimization-based Naked Mole Rat algorithm. When the movable target node falls within the span of the anchor node, an anchor node along with two nearby virtual anchors are chosen, and distance calculations between the anchor and target nodes are performed. Then, by using the Centroid formula, the co-ordinates of the target node are computed. These are further optimized by the WONMRA algorithm to minimize the localization error. The simulation results carried out in MATLAB proved that the localization error computed by WONMRA is minimum in contrast to other optimization algorithms.

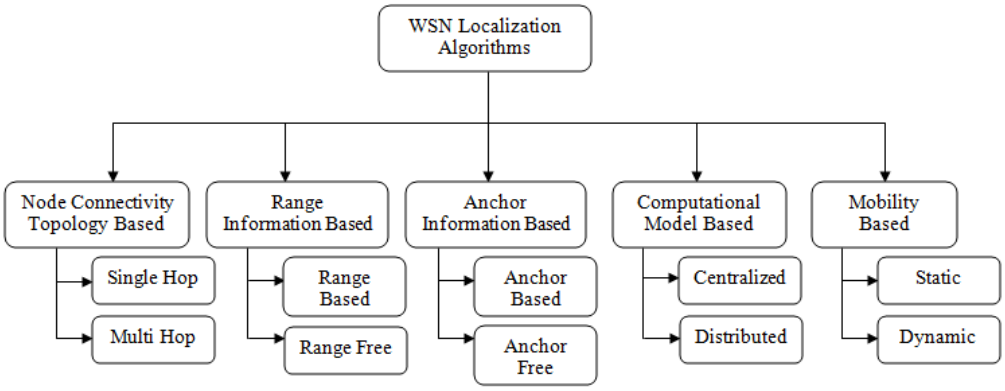

Figure 1. Localization algorithms.

The hybrid approach of the Whale Optimization-based Naked Mole Rat algorithm is used in this paper. The main cause of using the hybrid approach is that the WOA has weak exploitation operations despite its efficiency in searching the search space, whereas NMRA has weak exploration abilities, thereby causing it to become stuck in local optima. To resolve this issue, the worker phase of WOA comprises extra prospective equations that will significantly enhance the algorithm's capacity for searching globally. Additionally, the fundamental NMRA's mating factor parameter λ is crucial in regulating the algorithm's performance and needs to be inspected for self-adaptive algorithms. This work considers these two factors into account and utilizes the novel self-adaptive Whale Optimization-based NMRA in this work.

The main contributions of this work include the following:

- The state-of-art review on the localization techniques used to localize the sensor nodes in a 2D environment.
- A new approach of taking a single anchor along with virtual projection in six varying orientations to find the entire undetermined nodes is used. The single anchor node, along with two virtual nodes, is chosen to locate its position as soon as the target nodes fall within the span of the anchor node.
- The work utilized a novel Whale Optimization-based Naked Mole Rat Algorithm (WONMRA) to provide more accurate results.
- The WONMRA performance experiments on the Wireless Sensor Networks Localization problem, and the findings reveal that it has better convergence accuracy, the least localization error, and a strong optimization capability when compared with the other existing algorithms, including PSO, HPSO, BBO, FA, NMRA, and WOA.

The paper is categorized as follows: Section 2 includes a thorough survey of localization. The WONMRA approach with its algorithm is discussed in Section 3. Section 4 describes the localization approach employing an individual anchor node, Section 5 includes the numerous challenges in localization, Section 6 presents the discussion on Simulation results and experiments, and the conclusion along with future scope are included in Section 7.

2. Literature Review

The count of anchors in a sensor network is generally limited. The benefit of the anchor nodes is that we know where they are after they are deployed. Because of the price and complexity limits, certain node locations are unknown, as it is not possible to deploy every node with GPS functionality. The position of the anchor node is applied to estimate the position of these nodes. Many other approaches to localization have been proposed by researchers in recent years [13]. In this study, unknown nodes are approximated by applying distance measurements, and the evaluated location is optimized by making use of a meta-heuristic approach in a mobility-based scenario.

Various homogeneous as well as heterogeneous sensor nodes are included in WSN, with every node having the capacity to collect, measure, and transfer data to the node to which it is related before transferring to the sink node. The information sent and obtained is useful and instructive since it aids in pinpointing the actual location of the desired node. It would take a long time and be completely impossible to manually add position information to every node in many applications. WSN has recently attained remarkable advances in the field of wireless communications. The advancement in sensor network equipment covers a wide range of applications [13]. The node location has become a critical need for effective WSN applications. The variety of localization methods includes range-based and range-free procedures. TOA [14], TDOA, AOA [15], and RSSI [16] are examples of range-based approaches for determining the angle or distance among two neighbouring nodes.

Lee et al. [17] developed a novel method in which limited anchor nodes are stationed in the network. On the basis of change in the path, a novel approach to measure the distances is discovered by approximating the shortest path to evaluate their Euclidean distance. In anisotropic networks, limited anchors are necessary to achieve high accuracy. Garg et al. [18] suggested another strategy on the basis of RSSI for locating the movable node, with anchor nodes placed at the vertex and at the four corners of target nodes placed randomly. Graefenstein et al. [19] proposed an RSSI-based approach for calculating the distance between the anchor and destination nodes. Moreover, after obtaining distances from the various anchors and virtual anchors, the trilateration method was employed to determine the location. Sumathi and Srinivasan [20] explained an RSS-based anchor localization algorithm in which the target nodes' location was estimated using the least square method. Guo et al. [21] suggested a perpendicular intersection (PI) approach to localization on the basis of mobility. This strategy is unable to directly map distance from RSSI data. The node position was calculated using the PI's geometric link.

Kim and Lee [22] proposed a particle size update technique based on certain filters, and they evaluated the algorithm by applying simulations with data generated through on-site trials. Furthermore, the Kalman filter-based location, as well as mapping techniques for real-time localization, are known in the literature [23]. Many computational intelligence (CI) strategies were addressed by the researchers with the purpose of boosting the accuracy and lessening the complexity of a localization challenge. Genetic algorithms (GA), as well as other stochastic methods such as simulated annealing (SA), are used in the static scenario in the literature. To attain the lowest localization error, Kulkarni and Venayagamoorthy [24] put forward the localization method on the basis of particle swarm optimization (PSO) as an alternative to stochastic techniques. To optimize the nodes' position in the WSNs, Gopakumar and Jacob [25] suggested another new global swarm intelligence (SI)-based approach. The suggested approach streamlines the implementation process while using little memory, making PSO-based algorithms more suitable in constrained situations. The HPSO technique was developed as a quick convergence framework for optimizing the target node's position. In order to improve precision in the localization problem, biogeography-based optimization (BBO) can be applied [25,26]. Kumar et al. [27] suggested combining the BBO and the hybrid PSO (HPSO) for range-free BBO and range-free HPSO localization approaches in anisotropic WSN.

A computational intellect algorithm on the basis of particle swarm optimization was introduced for finding the locality of the moving target nodes [28–31]. With anchor nodes placed in the corners of the sensing field, the procedure is segregated into two parts. The first step includes the distance estimation approximations. The subsequent step assumes the anchor nodes virtually in six varied orientations at ideally 60° each to find the undiscovered nodes. By combining a PSO optimization method with Centroid computations at this point, the findings showed a faster convergence time. Binary PSO employed received signal strength indicator to compute the distance among the anchor and target nodes thereby enhancing the network lifetime with decreasing power utilization due to quicker convergence. Singh and Mittal [32] suggested a hybrid DA-FA approach for locating mobile target nodes in Wireless Sensor Networks by using only one anchor node. When compared to other techniques, such as PSO, FA, BBO, and HPSO, the findings show lower localization error and convergence rate. Mittal et al. [33] optimized the Cognitive Radio System to determine the best channels in the vicinity to avoid congestion and traffic in the network.

This work utilizes a new method of employing virtual anchor nodes in two dimensions using the Whale Optimization-based Naked Mole Rat Algorithm (WONMRA) [34] to locate undiscovered nodes. WONMRA is a newly developed optimization algorithm that improves computing time while simultaneously minimizing localization error.

3. Whale Optimization-Based Naked Mole Rat Algorithm (WONMRA)

Swarm optimization approaches like the Whale Optimization Algorithm (WOA) [35] and Naked Mole Rat Algorithm (NMRA) [36] give dependable results to optimization issues and are very encouraging algorithms despite their performance not being as stable as that of sophisticated hybrid and adaptive algorithms. The main cause is that the WOA has weak exploitation operations despite appearing to be efficient in searching the search space, whereas NMRA has weak exploration abilities, thereby causing it to be stuck in local optima. To address this issue, the worker phase of WOA comprises extra prospective equations that will significantly enhance the algorithm's capacity for searching globally. Additionally, the fundamental NMRA's mating factor parameter λ is crucial in regulating the algorithm's performance and needs to be inspected for self-adaptive algorithms. This work considers these two factors and utilizes the novel self-adaptive Whale Optimization-based NMRA with the following key features:

- The worker phase of NMRA is improved by utilizing the hybrid concept of WOA and NMRA.
- For carrying out the worker's phase, the actual NMRA equations [36] are utilized for the first half of iterations, and WOA's mathematical equations [35] are utilized for the second half.
- To make the algorithm self-adaptive and eliminate the need for user-driven parameter customization, the simulated annealing (sa)-based mutation operator is used for the major parameter (λ) of the fundamental NMRA.

WONMRA Approach: Its Requisites and Phases [34]

It is becoming harder and harder to decide which optimization method is best as new ones continue to appear. A single optimization technique is insufficient for performance evaluation of all domain research challenges, as demonstrated by the no free lunch (NFL) theory. Therefore, it is necessary to find new optimization techniques based on modifications that can help with the resolution of a range of actual optimization issues. The key justification for the addition of changes to the original algorithm is that every domain research challenge can have a different set of circumstances, including size, complexity, type (either limited or unconstrained), and dimension. It is challenging for researchers to develop better versions and provide findings that are acceptable because of the high dimensional difficulties and abundance of local minimal solutions. In this case, fundamental NMRA reduces algorithmic efficiency and suffers from weak exploration features. To ensure that trustworthy exploration operations are carried out and to keep the algorithm from being stuck in the local minima, a new equation for the worker phase must be created. The addition of these new equations must be performed so as to avoid altering the fundamental structure of the NMRA in any manner.

So, the WOA mathematical equations are included in the fundamental NMRA equations, and the entire search is run through a predetermined number of iterations. Through the generation of random solutions and thorough investigation of every inch of the search area, the extra equations obtained from WOA are utilized to enhance the exploration properties of the suggested algorithm. Additionally, the mating factor λ parameter is altered to become self-adaptive, negating the need for user interaction. It is assumed that the NMRA's original structure would remain intact.

The following Equation (1) [36] is utilized to initialize the search candidates randomly within a given interval at the beginning of the process.

$$W\,N_{i,j} = W\,N_{min,j} + rand(0,1) \times \left(W\,N_{max,j} - W\,N_{min,j}\right) \tag{1}$$

In the above equation, $i\,\epsilon\,[1,\ 2,\ 3\ldots n]$, n represents the count of search candidates(mole-rats), $j\,\epsilon\,[1,\ 2,\ 3\ldots d]$; d is optimization problem dimension; $W\,N_{min,j}$, and $W\,N_{max,j}$ are the lower and upper boundaries of the test problem; $W\,N_{i,j}$ represents the solution of the ith search candidate for the jth dimension; and $rand(0,\ 1)$ is randomly distributed in the $range$ $[0,\ 1]$.

- Exploration Phase (Worker): The worker phase of WONMRA employs two randomly selected search pool solutions to locate a nearly optimum solution. It has been found after thorough investigation that the worker phase is less reliable and that more work is required to enhance its functional features. Therefore, the worker phase of the NMRA is enhanced by embracing the intrinsic qualities of WOA. So, the following Equations (2)–(5) [34] of WOA are included in WONMRA, and the actual structure of the algorithm remains intact.

$$\overset{\rightarrow t+1}{X} = \overset{\rightarrow}{H'}.e^{bl}.cos(2\pi l) + \overset{\rightarrow *t}{X} \tag{2}$$

$\left|\overset{\rightarrow}{H'} = \overset{\rightarrow *t}{X} - \overset{\rightarrow t}{X}\right|$ indicates the difference between the whale and the best candidate for the prey. The logarithmic spiral form is represented by a constant value for b, and the random distribution of l between -1 and 1. It is considered that there is a 50% possibility of choosing a spiral model or a shrinking mechanism for carrying out exploitation, i.e., the prey attacking. This can be quantitatively stated as the final equation:

$$\overset{\rightarrow t+1}{X} = \begin{cases} \overset{\rightarrow *t}{X} - \vec{F}.\vec{H} & if\ u < 0.5 \\ \overset{\rightarrow}{H'}.e^{bl}.cos(2\pi l) + X^{*t} & if\ u \geq 0.5 \end{cases} \tag{3}$$

The random number lies uniformly in the $range$ $[0,1]$.

$$\vec{H} = \left|\vec{G}.\vec{X}_{rd} - \overset{\rightarrow t}{X}\right| \tag{4}$$

$$\overset{\rightarrow t+1}{X} = X_{rd} - \vec{F}.\vec{H} \tag{5}$$

X_{rd} represents the randomly selected search candidate from the whole population.

- Exploiting Phase (Breeder): The actual fundamental NMRA structure is utilized to carry out this phase of WONMRA. Breeder rats can only mate with the queen in the global solution. It follows that the exploitation operation will take place at the same time as the breeding phase. Exploitation is primarily used in the global search phase because it searches for a solution that is almost identical to the best solution currently in use and is expected to yield a global solution towards the conclusion of the iterations. There have been no modifications made to the breeder phase of the new proposed method (WONMRA), which is the same as the NMRA phase.
- Parameter adaptation: The suggested algorithm (WONMRA) heavily relies on the mating factor λ of the fundamental NMRA. In the fundamental NMRA, this parameter is specified by random values; hence, it needs to be changed to yield better results. Thus, this parameter has been adjusted so that it does not require any adjustments at

the user level. Thus, the best randomization results are obtained when parameter λ is implemented using simulated annealing (sa)-based mutation [33]. The following is the generalised equation [33] that was utilized to carry out the sa-based mutation operation:

$$\alpha_k = \alpha_{min} + (\alpha_{max} - \alpha_{min}) \times b^{k-1} \tag{6}$$

k, α_{max}, and α_{min} are constants in the $range[0, 1]$, the value of b is 0.95.

- Greedy Selection: The WONMRA's selection phase is regarded as its last stage. The current work applies a greedy selection strategy, wherein a freshly generated solution surpasses the solution from the prior generation and is replaced as the current local best solution.

Equation (7) [33] provides the selection strategy for a generalised minimization process with fitness $f\left(W\ N_t^i\right)$ for the $W\ N_t^i$ solution.

$$W\ N_{new}^{t+1} = \begin{cases} W\ N_{new} & if\ \ f(W\ N_{new}) < f\left(W\ N_t^i\right) \\ W\ N_i^t & otherwise \end{cases} \tag{7}$$

The pseudocode of WONMRA is explained below in Algorithm 1.

Algorithm 1: Pseudocode of WONMRA

```
Start:
Inputs: Define the random population of NMRs: (n)
    Decide count of breeder mole-rats(B) = n/5
    Decide count of worker rats(W) = n − B
    Initialize breeding probability value (bp)
    Define problem's dimension (d)
Output: Evaluate best search candidate (N_best)
while t ≤ maximum iteration count (t_max)
    for i = 1:W
        if Current iteration ≤ t_max/2
            execution of NMRA worker phase
        else
            execution of WOA equations by (2), (3), (4) and (5)
        end if
    end for
    for i = 1:B
            if rand(0,1) > bp
                execution of breeder phase
        end if
    end for
        perform greedy selection by Equation (7)
        update λ using sa mutation operator
        unite new mole rats (W &B)
        update (N_best)
        increment t
End while
    Save N_best
    Stop
```

4. Localization Employing Exclusive Anchor Node

To locate moveable target nodes, a single anchor node is used. The unknown target nodes are distributed randomly. The entire sensor area is divided into circular fields and is located within the anchor node's span. A beacon wave is sent by the anchor node to let the moveable target nodes find themselves individually. Movable target nodes first watch the beacon signal and gather the RSS data from the anchor node when they arrive under the span of the anchor node. The distance between the anchor and target nodes is calculated after collecting RSS data. In order to investigate the localization of the moveable target nodes, six virtual anchors are projected hexagonally at a 60° angle with the anchor node, and two of them will be selected at random as a minimum of three reference nodes is required. In this study, all nodes are assumed to have identical hardware configurations and transmission ranges. Figure 2 explains the general localization procedure.

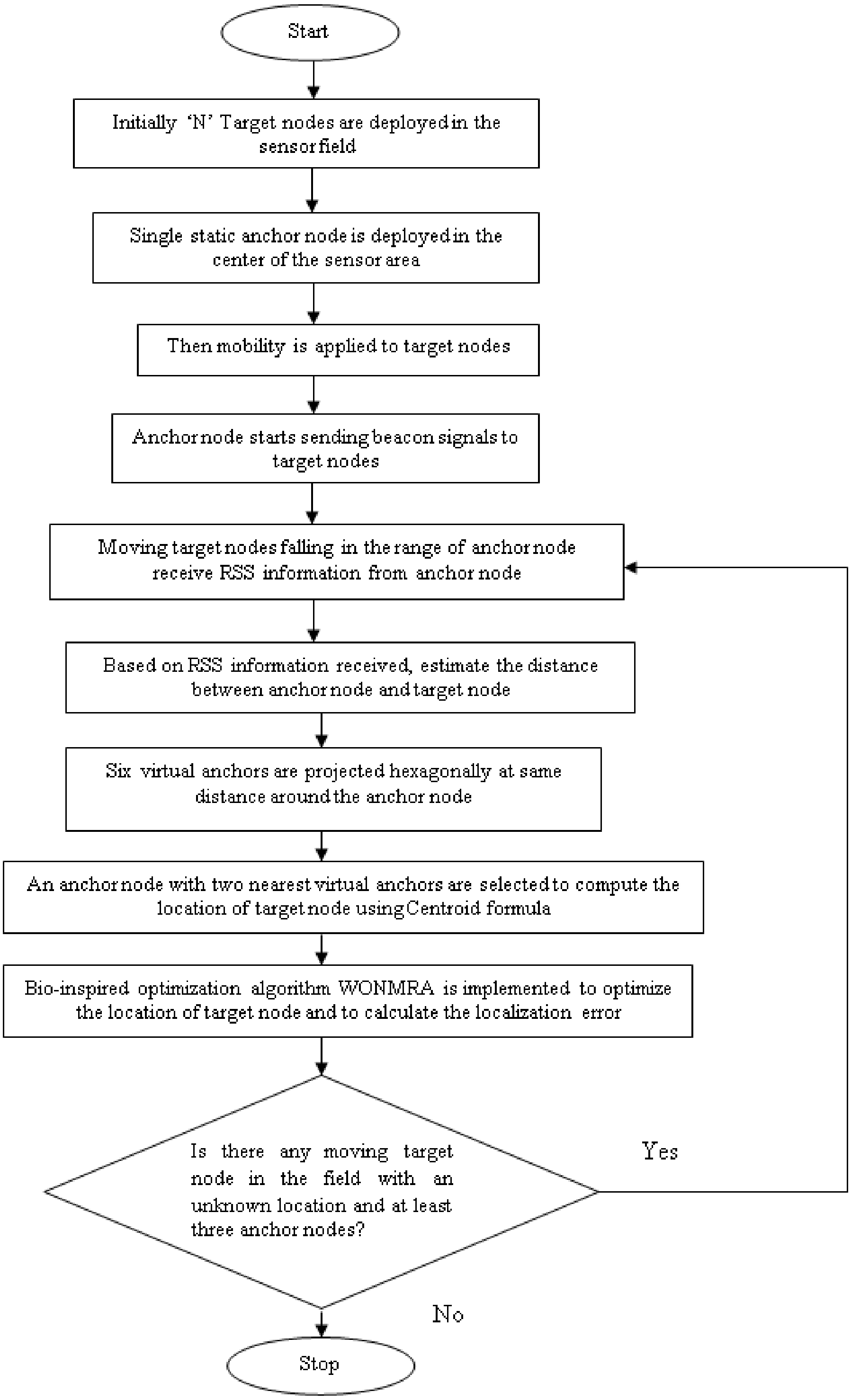

Figure 2. Process of localization.

The localization of the target node involves the following steps:

1. The 15×15 m^2 area is filled with one anchor node and 'N' number of target nodes.

2. The mobile target nodes falling within the exclusive anchor node's span keep note of the distances between the anchor and the target node as well as two virtual anchors nearby since a minimum of three reference nodes count is taken as three to find unknown nodes. Figure 3 displays the idea of the sensor field.
3. Then, WONMRA is used to assess unknown nodes' positions.

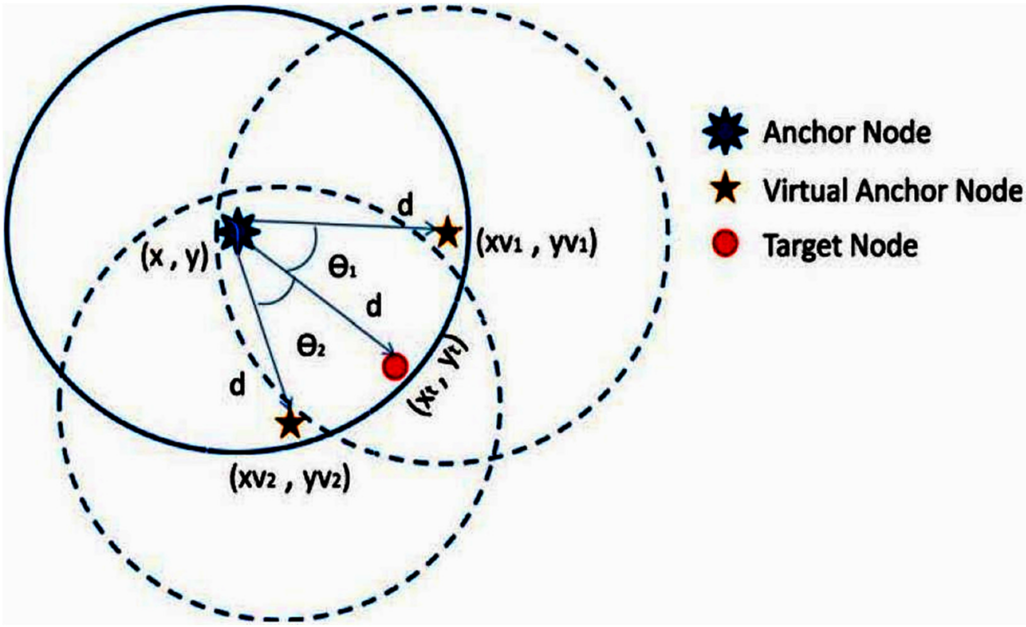

Figure 3. Sensor field representation.

Figure 3 depicts the distance between the anchor node and each moving target node. Each anchor node uses two virtual anchor nodes as a minimum of three reference nodes are being taken to compute the two-dimensional position of the target node.

$$d_i = \sqrt{(x_t - x)^2 + (y_t - y)^2} \tag{8}$$

Here, (x, y) denotes the current locality of the anchor node, and (x_t, y_t) represents the locality of the target node. Equation (9) estimates the Centroid position, and its representation is shown in Figure 4.

$$x_c,\ y_c = \left(\frac{x + xv_1 + xv_2}{3},\ \frac{y + yv_1 + yv_2}{3}\right) \tag{9}$$

The application of WONMRA to determine the parameters of a target node indicated by (x_s, y_s) is shown in Figure 5. The objective is to decrease the gap between the calculated and real node co-ordinates, which is stated in Equation (10):

$$f(x_s,\ y_s) = \frac{1}{M}\sum\left(\sqrt{(x_e - x_i)^2 + (y_e - y_i)^2} - \hat{d_i}\right)^2 \tag{10}$$

where M represents the count of beacons taken as greater than three in this study, (x_e, y_e) represents the estimated position of the target node, and (x_i, y_i) represents the locality of anchor node i in the neighbourhood of the target node.

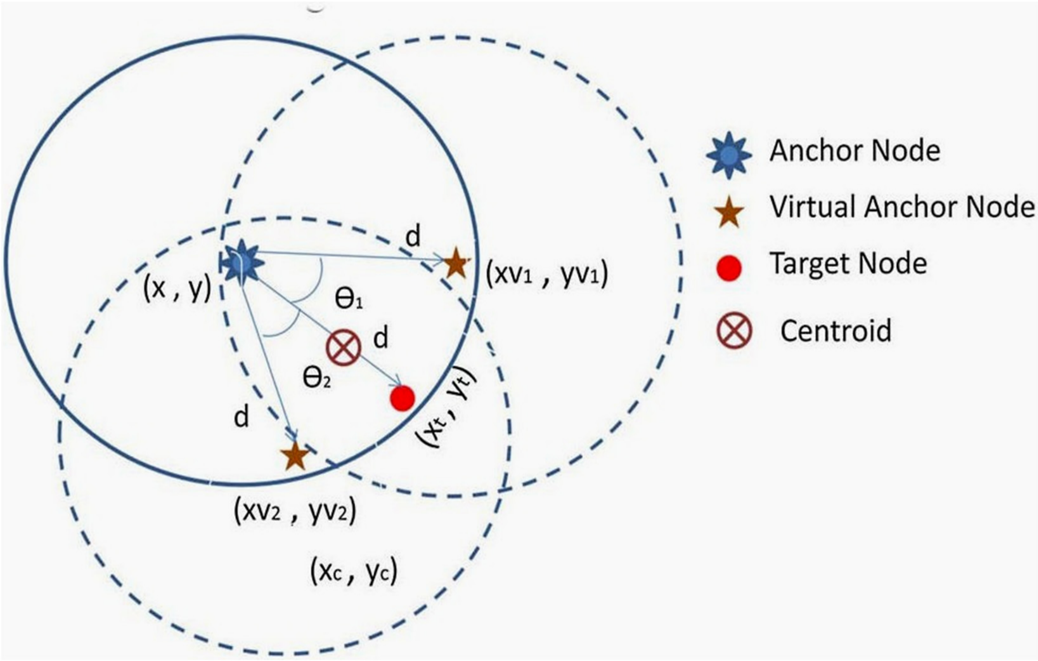

Figure 4. Centroid calculation.

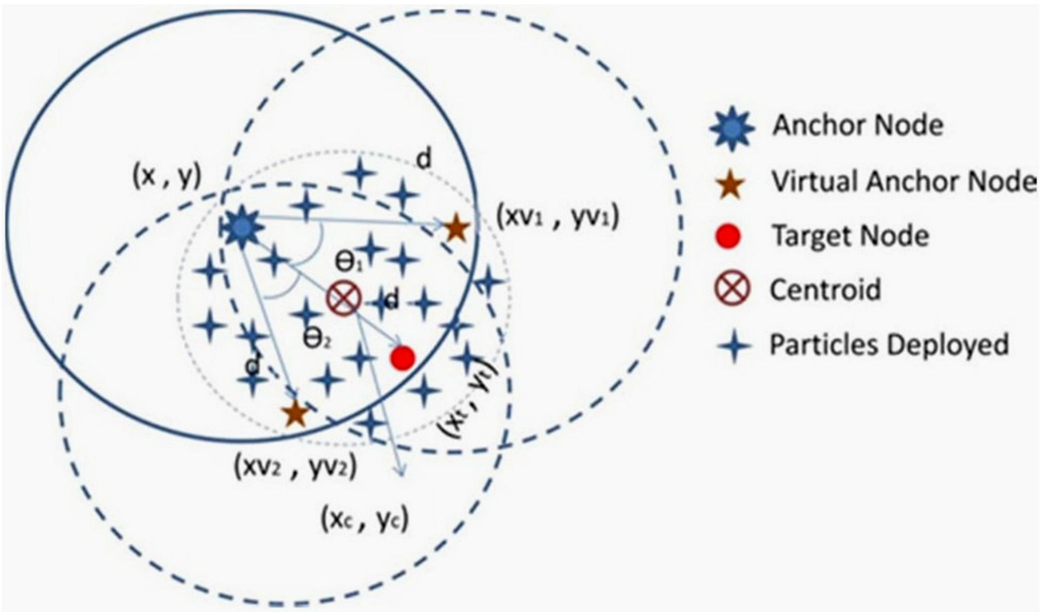

Figure 5. WONMRA implementation around Centroid.

The localization error is computed by employing Equation (11) and is depicted in Figure 6.

$$E_t = \frac{1}{N_L} \sum \sqrt{(x_e - x_t)^2 + (y_e - y_t)^2} \tag{11}$$

The ideal position of the target node is computed for WONMRA till the stopping condition is reached.

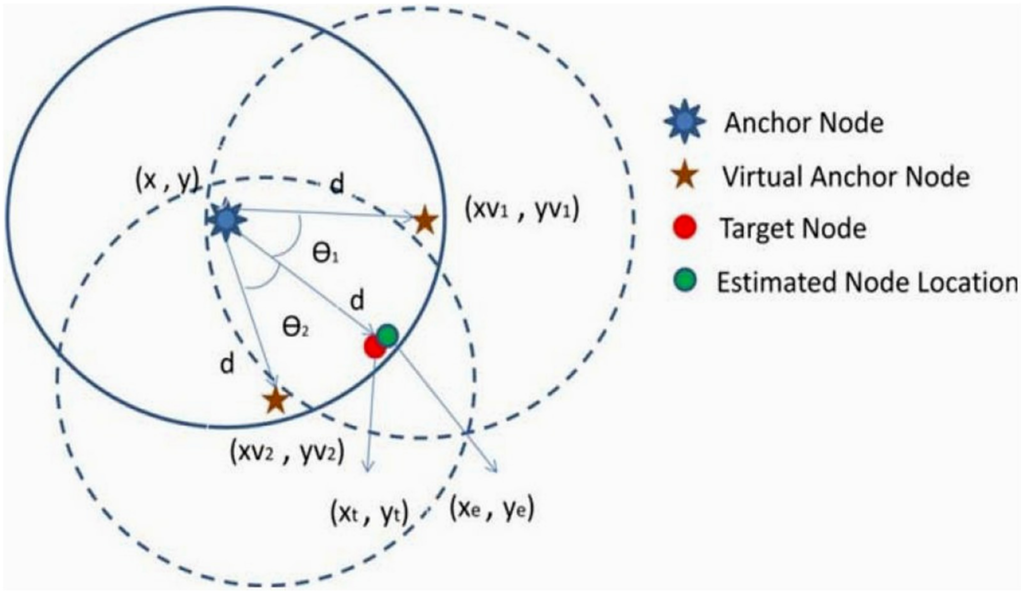

Figure 6. Error estimation using WONMRA.

5. Challenges in Localization

- Resource limitations: Nodes need to be extremely simple to deploy and inexpensive to manufacture. The designers need to make a concerted effort to reduce the localization algorithms' power, hardware, and deployment costs. It must also be simple to deploy.
- Terrain irregularities and environmental barriers: These factors can also have a significant negative impact on localization. For example, in an outdoor setting, large boulders may block the line of sight, making TDoA ranging impossible, or they may interfere with radio signals, causing errors in RSSI ranges and erroneous hop count ranges. Measurements can also be hampered indoors by walls. Since genuine deployments are likely to encounter all of these problems, localization systems ought to be equipped to handle them.
- Security: The primary concern in localization is security since, when data are moved from a beacon node to an anchor node, any insecure mobile beacons that act as original mobile beacons may transmit misleading messages, causing an error that could be detrimental to computation.
- Density of Nodes: The node density affects a lot of localization algorithms. For example, in order to ensure that the hop count approximation for distance is accurate, hop count-based methods generally require high node density. When a region's beacon density is insufficient, algorithms that rely on beacon nodes malfunction. Implicit density assumptions are crucial when developing or evaluating algorithms since, in certain cases, achieving high node density might be costly, if not completely impractical.

6. Simulation Parameters, Results, and Analysis

The simulations were carried out in MATLAB, taking 20 movable target nodes along with a single anchor node by employing the different optimization algorithms, including FA, BBO, PSO, HPSO, NMRA, WOA, and WONMRA. On a MacBook Air having RAM 4 GB and an i5 processor, the simulations were run. The anchor node is kept in the centre of the 15×15 m^2 sensor area and is stationary. The anchor node keeps sending beacon signals to all the nodes in the sensor area. The target nodes are dispersed across the sensor area initially and their random locations are taken. Then, mobility is applied to target nodes. Whenever the movable target node enters into the anchor node's span, the signal is received from the anchor node, the received signal strength value is taken at the target node, and six virtual nodes are projected at different orientations of 60° in all directions. Then, the anchor and two virtually projected anchor nodes from six are considered to compute the co-ordinates of the undiscovered node. When virtual anchor nodes are employed, LOS problems can also be minimized. Numerous simulations are performed using FA, BBO, PSO, HPSO, NMRA, WOA, and WONMRA optimization algorithms in order to assess the different optimization algorithms' effectiveness in achieving accuracy in localizing the target node. On a sensor area of 15×15 m^2, simulations were run. Even though virtual anchors more than six can be employed, in this case six virtual anchors are required to satisfy the condition for selecting the three closest anchor nodes when locating nodes in a two-dimensional scenario.

Table 1 displays the co-ordinates for the anchor node and virtual anchor nodes. Table 2 displays the calculated distance between the target nodes, anchor nodes, and virtual anchor nodes. In this work, the anchor node is used first, and five different movements are taken into consideration for the motion of all target nodes.

Table 1. Virtual anchor nodes and anchor node co-ordinates.

Co-ordinates	AN	VAN1	VAN2	VAN3	VAN4	VAN5	VAN6
X	7.5	11.131	6.310	3.539	5.565	8.810	11.527
Y	7.5	10.464	10.899	6.841	4.464	3.953	5.639

Virtual anchor node (VAN), anchor node (AN).

Table 2. Distance estimation between anchor node and target nodes deployed in the area.

S. No.	AN	VAN1	VAN2	VAN3	VAN4	VAN5	VAN6
TN:1	6.101	7.988	9.866	8.769	6.028	1.598	3.376
TN:2	5.248	5.334	8.679	9.237	9.421	6.342	1.365
TN:3	8.576	9.345	4.784	8.278	11.775	12.461	12.718
TN:4	4.928	7.459	8.877	8.455	6.225	3.528	3.192
TN:5	9.468	5.039	9.875	11.745	12.442	12.219	6.457
TN:6	5.969	5.232	2.739	7.221	10.348	10.844	7.953
TN:7	5.739	8.319	10.543	10.314	7.723	3.454	2.589
TN:8	6.286	1.777	5.320	8.993	10.351	9.289	5.406
TN:9	9.549	11.485	11.133	7.631	4.774	9.420	12.363
TN:10	7.465	9.354	12.463	11.432	10.131	5.357	1.784
TN:11	7.378	7.256	10.189	11.741	11.693	7.873	2.082
TN:12	6.656	5.585	1.651	6.732	10.155	11.395	8.787
TN:13	8.313	11.634	11.877	7.237	3.521	7.631	10.730
TN:14	8.289	12.689	12.212	7.934	3.788	7.267	10.722
TN:15	5.497	5.123	8.791	10.859	10.461	7.152	1.576
TN:16	5.763	7.588	10.446	10.110	7.333	3.128	2.893
TN:17	9.214	5.647	10.665	11.431	13.615	10.646	4.797
TN:18	4.433	3.189	3.210	6.389	8.727	9.235	6.786
TN:19	9.235	12.861	10.865	6.101	6.581	9.899	12.438
TN:20	6.469	9.756	5.989	1.545	7.457	10.121	10.479

Target node (TN), virtual anchor node (VAN), anchor node (AN).

Table 3 lists the strategic parameters for each algorithm, including FA, PSO, BBO, HPSO, NMRA, WOA, and WONMRA. Each moveable target node will employ the FA, PSO, BBO, HPSO, NMRA, WOA, and WONMRA optimization strategies to discover on its own within the suggested framework.

The test is administered utilizing a mobility-based environment. The mean of the localizing error specified in Equation (8) is referred to as a fitness function.

Figures 7–13 display the results of localization using a variety of optimization approaches, including FA, PSO, BBO, HPSO, NMRA, WOA, and WONMRA. Table 4 displays network parameters established in the network and the results of localization using a variety of optimization approaches. It shows the accuracy achieved with each optimization algorithm by calculating the mean localization error and number of target nodes localized in the network. As depicted in Figures 7–13, the optimization techniques were run for five different movements following a given period. The process is repeated for each interval. Compared to various meta-heuristics, WONMRA has the lowest localization error; followed by HPSO; then PSO, BBO, NMRA, WO; and lastly, FA has the highest localization error.

Table 3. Parameters selection for optimization algorithms.

Algorithm	Parameters Values
FA	$M = 20$; $D = 2$; $I_{\max} = 50$; $\alpha = 0.2$; $\gamma = 0.96$
PSO	$M = 20$; $D = 2$; $I_{\max} = 50$; $w = 0.729$; $c_1, c_2 = 2$
BBO	$M = 20$; $D = 2$; $I_{\max} = 50$; $p_m = 0.05$
HPSO	$M = 20$; $D = 2$; $I_{\max} = 50$; $c_1, c_2, c_3 = 1.494$; $w = 0.729$; $\eta = 0.1$
NMRA	$M = 20$; $D = 2$; $I_{\max} = 50$; $\mathrm{bp} = 0.05$; $\lambda = rand\ [0, 1]$
WOA	$M = 20$; $D = 2$; $I_{\max} = 50$;
WONMRA	$M = 20$; $D = 2$; $I_{\max} = 50$; bp = 0.05; λ = simulated annealing mutation operator (adaptive)

Here, D denotes the problem dimensions, M refers to the population size, $I_{\max}$ is the number of iterations.

Table 4. Comparative analysis of meta-heuristic algorithms in determining error in localization.

Algorithm Used	No. of Movements	Localized Target Nodes	Transmission Range	Maximum Localization Error	Minimum Localization Error	Average Error
PSO	1	20	10	1.8913	0.1523	0.6845
	2	20	10	3.7321	0.2287	1.1323
	3	20	10	2.8756	0.1310	0.8276
	4	20	10	1.9012	0.2210	0.5943
	5	20	10	1.3534	0.1589	0.7512
HPSO	1	20	10	0.7934	0.1145	0.2267
	2	20	10	0.9932	0.0971	0.3376
	3	20	10	0.5745	0.0421	0.3398
	4	20	10	0.6912	0.2110	0.3462
	5	20	10	0.5423	0.2165	0.2234
BBO	1	20	10	1.4456	0.0276	0.3890
	2	20	10	1.4765	0.0913	0.8213
	3	20	10	1.4745	0.0308	0.6915
	4	20	10	1.4623	0.0321	0.7947
	5	20	10	1.5512	0.0543	0.9387
FA	1	20	10	4.6073	0.3834	2.3534
	2	20	10	5.7834	0.5813	3.0586
	3	20	10	4.7565	0.0292	2.5695
	4	20	10	5.1610	0.2402	3.1367
	5	20	10	4.5801	0.1990	2.5648
NMRA	1	20	10	1.5467	0.8789	1.4577
	2	20	10	3.6785	0.9134	1.6754
	3	20	10	2.5643	0.5642	1.8061
	4	20	10	2.8976	0.4536	1.4532
	5	20	10	3.4321	0.1254	0.9832
WOA	1	20	10	5.4563	0.0781	0.7861
	2	20	10	4.8976	0.5671	0.3425
	3	20	10	3.2341	0.4561	1.8976
	4	20	10	2.6759	0.8796	1.0432
	5	20	10	1.5672	0.8690	1.0562
WONMRA	1	20	10	0.5518	0.0943	0.2284
	2	20	10	0.6254	0.0687	0.3207
	3	20	10	0.5945	0.0289	0.2946
	4	20	10	0.6198	0.1897	0.2862
	5	20	10	0.4876	0.1789	0.1999

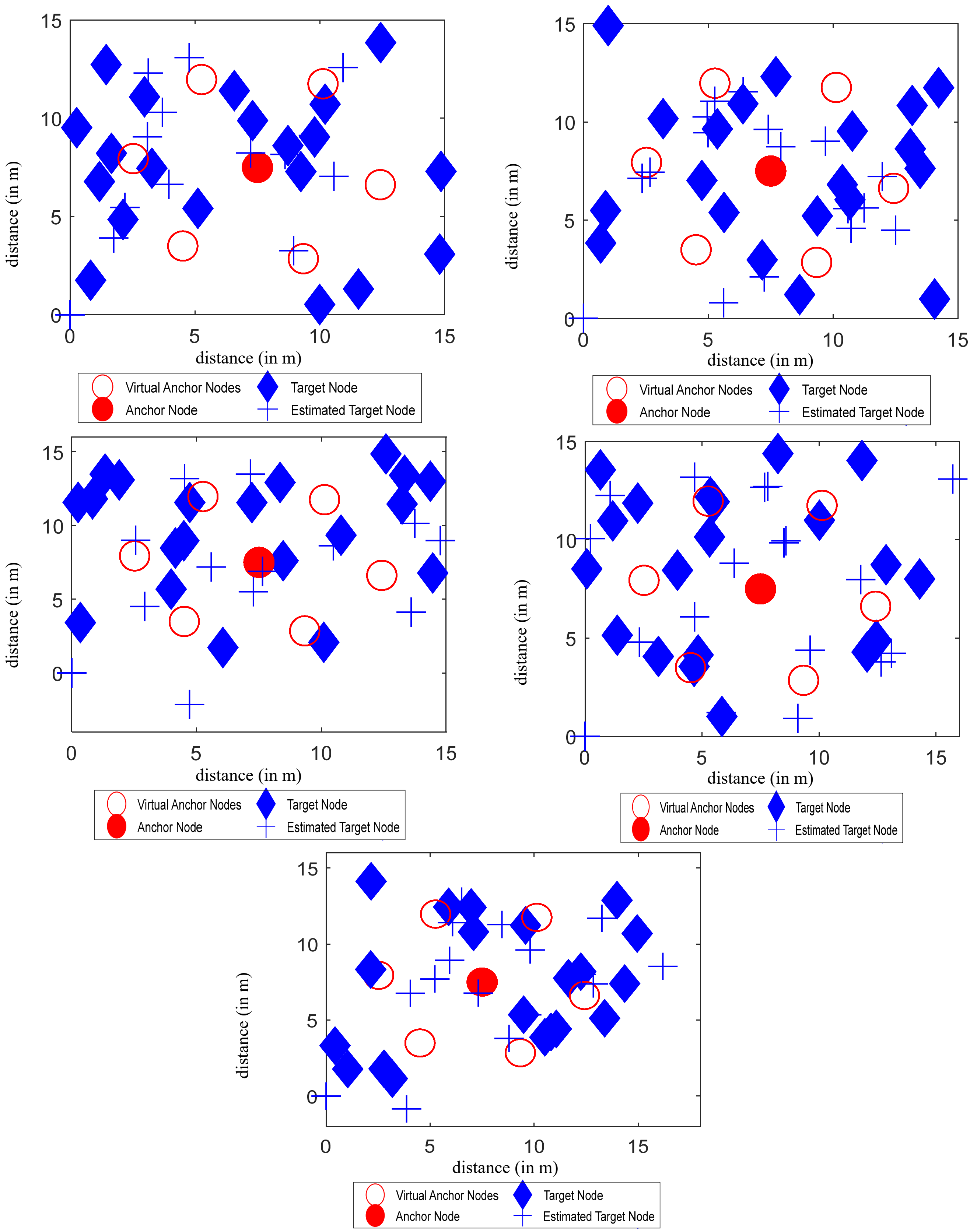

Figure 7. Node localization using FA.

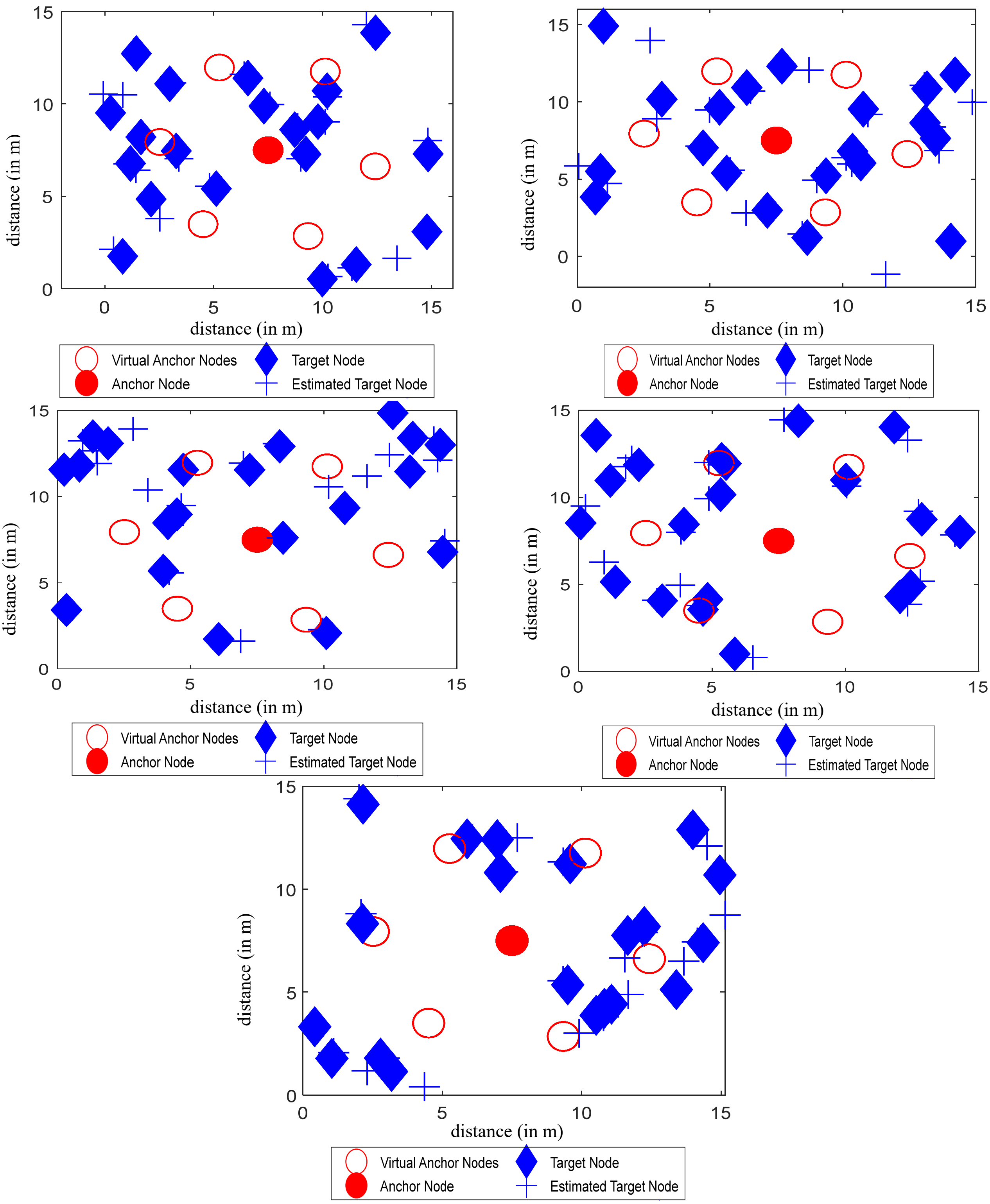

Figure 8. Node localization using PSO.

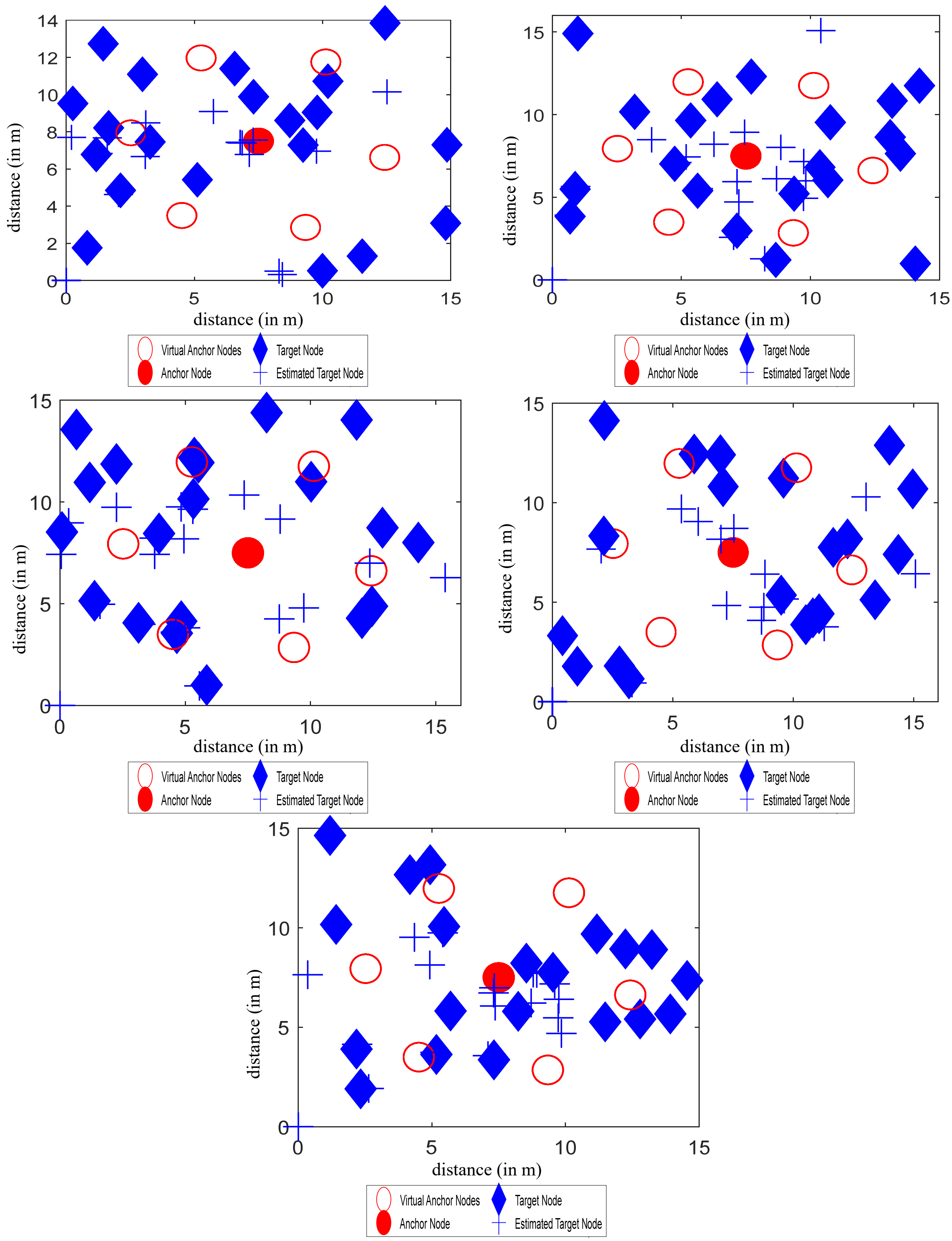

Figure 9. Node localization using BBO.

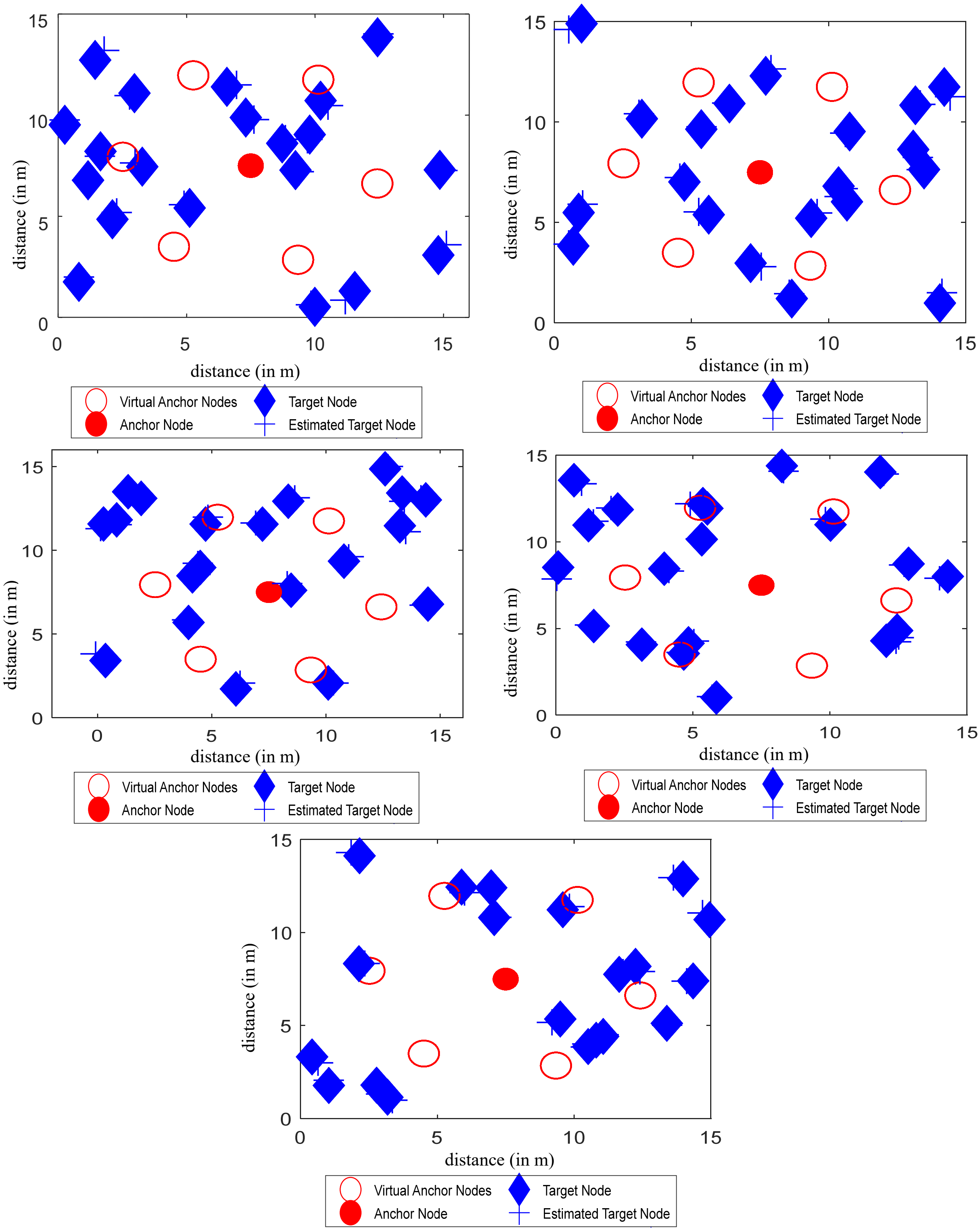

Figure 10. Node localization using HPSO.

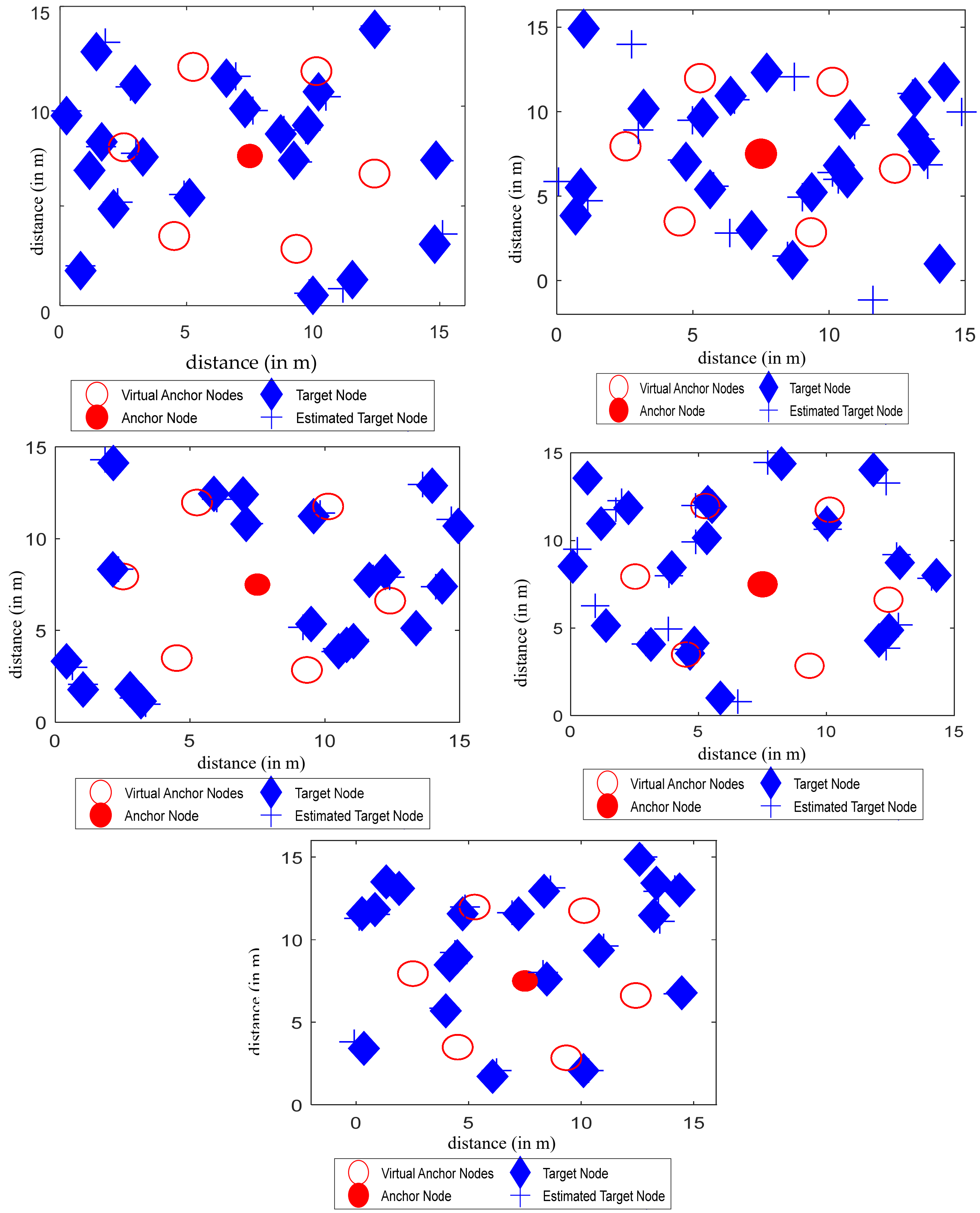

Figure 11. Node localization using NMRA.

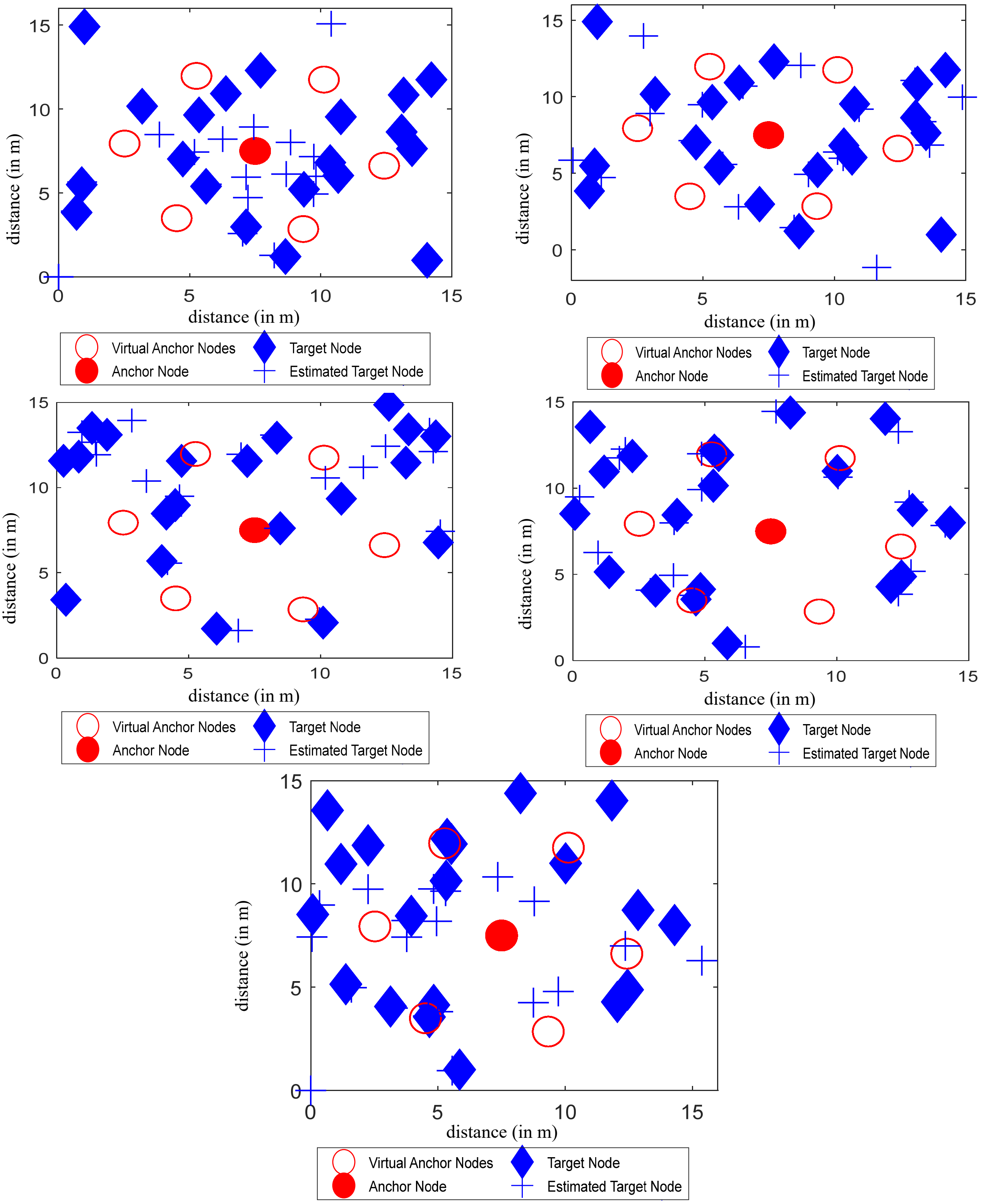

Figure 12. Node localization using WOA.

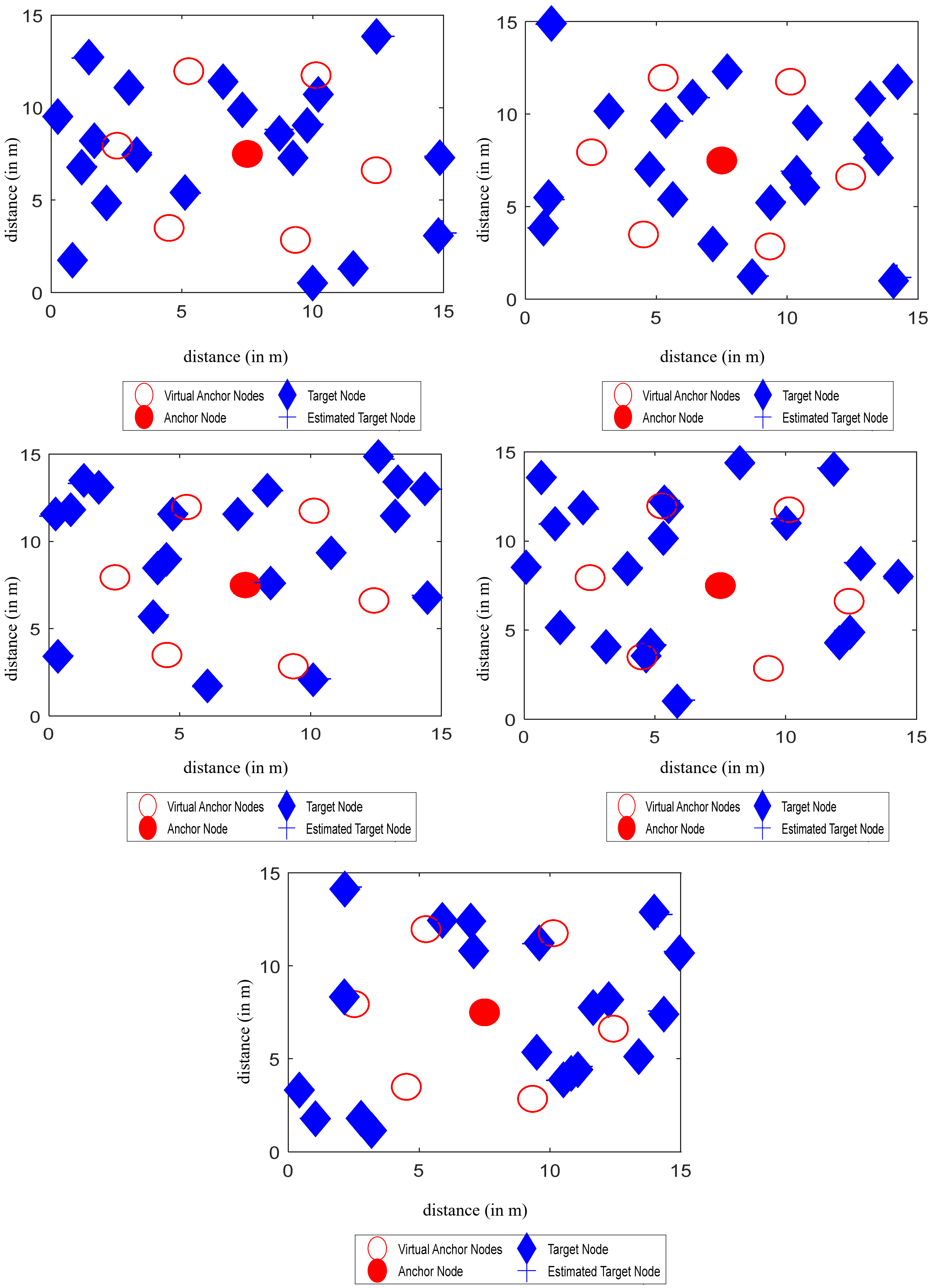

Figure 13. Node localization using WONMRA.

The best anticipated localized node position is indicated in the fifth run for each optimization approach by a "+" sign in Figures 7–13.

7. Conclusions

Localization is one of the most urgent issues with WSNs. It is important to trace the occurrence of a particular event with the help of sensor nodes deployed in the 2D as well as 3D Wireless Sensor Networks. For this reason, we need anchor nodes that have GPS installed in them. However, all the nodes cannot have GPS installed in them because that will increase the cost of the network. One thing that can be performed is the minimization of the count of anchor nodes in the network and the use of these anchor nodes as a reference for the calculation of co-ordinates of other nodes in the network. In many research papers, 2–3 anchor nodes are used to identify the location of unknown target nodes. But this work is carrying out localization utilizing a single anchor node and its projection using WONMRA at six different orientations within the circle. Two virtual anchor nodes are chosen together with an anchor node when a target node enters the anchor node's span because, at the minimum, three nodes are needed to locate the target node's 2D parameter values. Then, the error in localizing the nodes is computed by employing the meta-heuristic techniques FA, BBO, HPSO, PSO, NMRA, WOA, and WONMRA, and the results showed that the WONMRA excels with respect to mean localization error when compared to competing approaches. It has a minimum mean localization error of 0.1999, and the error computed by HPSO is 0.2234, which is in close proximity to WONMRA but is not the least value. Applications for this algorithm include tracking animals, logistics, and locating people in coal mines. For better accuracy and faster convergence, a different meta-heuristic technique can be used in the future.

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