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NODE LOCALIZATION BASED ON ANCHORS NODES IN WIRELESS SENSOR NETWORK

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Master Thesis

Supervisor

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NODE LOCALIZATION BASED ON ANCHORS NODES IN WIRELESS SENSOR NETWORK

by

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This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Mustafa Qays Bahaulddin Bahaulddin

DEDICATION

To My Beloved Family (My Dad, Mom, Brothers and Sister), To My Teachers In The Past, Present And Future. To My Asst.Prof.Dr.Sefer KURNAZ, To My Friends And To All Those Who Truly Believed In Me And Never Let Me Down Throughout The Way.

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My Thanks And Appreciation To My Supervisor Asst.Prof. To His Attention, Support, Patience To Me Throughout The Period Of This Study As Well As My Thanks To My Family, Who Was Supported For Me All The Time And Also To My Friends Who Help Me Throughout These Years.

ABSTRACT

NODE LOCALIZATION BASED ON ANCHOR NODES IN WIRELESS SENSOR NETWORK

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WSNs are currently utilized to observe an extended range of health-care, environmental, public, and military demands. In the medical field in general and the field of wireless medical sensor and in the different centers of the hospitals of the University of Oslo, they completed the implementation and development of six different sensors. These six devices represent a breakthrough in the medical field, including the wireless pressure transducer, accelerometer, pulmonary air flow meter, temperature sensor and more. It is also possible to develop the military field in this type of wireless devices such as sensors of energy consumption, security, resettlement and other military purposes. WSN is formed of a combination of points expanded in a domain, every point receives data and transmits them to the central location (named a base station) where collected data can be processed and analyzed. Find the position of a node has been a significant problem in WSN. Nodes localization in a WSN seeks to define the directions of different points with the assistance of recognized points. The accuracy of wireless networks can be clearly affected by the number of points that have been identified and localized correctly. In this paper, we employed and analyzed known methods, namely PSO and BOA with the proposed one. The simulation conducted out by using a MATLAB application, and outcomes prove that the suggested method gain higher accuracy and less error than other methods.

Keywords: WSN, PSO, BOA, Anchor Nodes, SSA and Localization methods.

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LIST OF ABBREVIATIONS

WSN	:	Wireless Sensor Network
PSO	:	Practical Swarm Optimization
BOA	:	Butterfly Optimization Algorithm
SSA	:	Salp Swarm Algorithm
FA	:	Firefly Algorithm
GWO	:	Grey Wolf Optimization

1. INTRODUCTION

1.1 INTRODUCTION OF WSN

WSN consist of a set of randomly distributed and independent sensors, using wireless technologies to send and receive data. WSNs are considered to be the most important types of wireless networks, are used in various applications such as monitoring of health, environment, traffic, ports, military operations and other important applications [1].

Sensor networks operate on a wide range of civilian, military and medical applications. The sensors are distributed in remote areas where each of them collects and transmits data on a main station called the source node. The base station is a key point through which data are analyzed and used optimally. Each sensor point generally consists of a sensor module, a processing unit, a transmitter and a receiver, and a very small battery. The function of any sensor is summarized in three key words: communication, sensing and processing. We can see the inner details of each sensor through the figure (1.1).

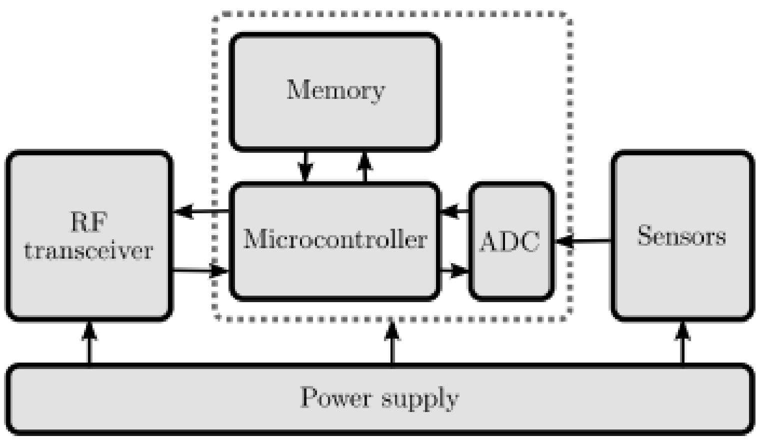

Figure 1.1: A typical sensor node architecture[2]

There are many types of sensors that have many uses. Among these devices, thermal sensors are used to measure temperature changes in the atmosphere, homes or in some industries. Also among these devices, sensors for sound waves can be used in water and air and have many uses. There are also mechanical sensors used to detect changes in different materials if they are solid or liquid but must be connected to the material directly. Also available in the market are magnetic sensors used in factories and laboratories for metal detection of non-contact material. Finding an unknown location has been a significant challenge in WSN. The data recorded from a sensor is only helpful when the status of that sensor is located [1].

In the purpose of WSN, the sensor points sight and describe the issues of concern which container be observed while the location of destination points describing the situation is identified. The evaluation of the node connections is one of the several critical problems of WSN and is recognized as a finding location dilemma [2] [3]. The approach of point locating position can ascertain and follow points. Data accumulated at the sink or base station may be insignificant to the user without positioning knowledge of the points in the search domain. The positioning can be determined as the measurement of the location of the unexplained sensor points declared as objective points using the identified location of the sensor points described as reporter points depend on the estimation like TVA, TOA , MLH and AOA. [1].

Finding point location or position problem of sensors network can be fixed by applying (GPS) with every point, but this is not preferred due to power, price and capacity problems. It still does not operate perfectly indoor. So, a valid and reliable choice is needed to locate the unknown points. Several non-GPS positioning methods can be utilized which is classified into RF and RB methods [4].

RB positioning methods utilize peer-to-peer range calculation or angle-based calculation among points. In this, the position is determined with the advice of reporter point (whose location is identified). RF positioning method do not need area information among the destination point and reporter point but depend on knowledge. RB method produces more efficiency as balanced to range-free positioning methods, but they are not so efficient [5] [6].

1.2 PROBLEM STATEMENT

The discovery and identification of sensor locations in the sensor networks and in various places is an important issue and concerns the researchers. This problem can be called in the field of wireless networks as the localization problem as shown in the figure (1.2). This is a problem that has an important dimension because sometimes we cannot access sensors in areas such as deep forests, seas or oceans. In the WSN there will be many points in random positions, and they are deployed in different locations and are densely defined. Therefore, due to these conditions, the problem of finding and locating the different points of the sensors in relation to some predefined sensors must be solved [6].

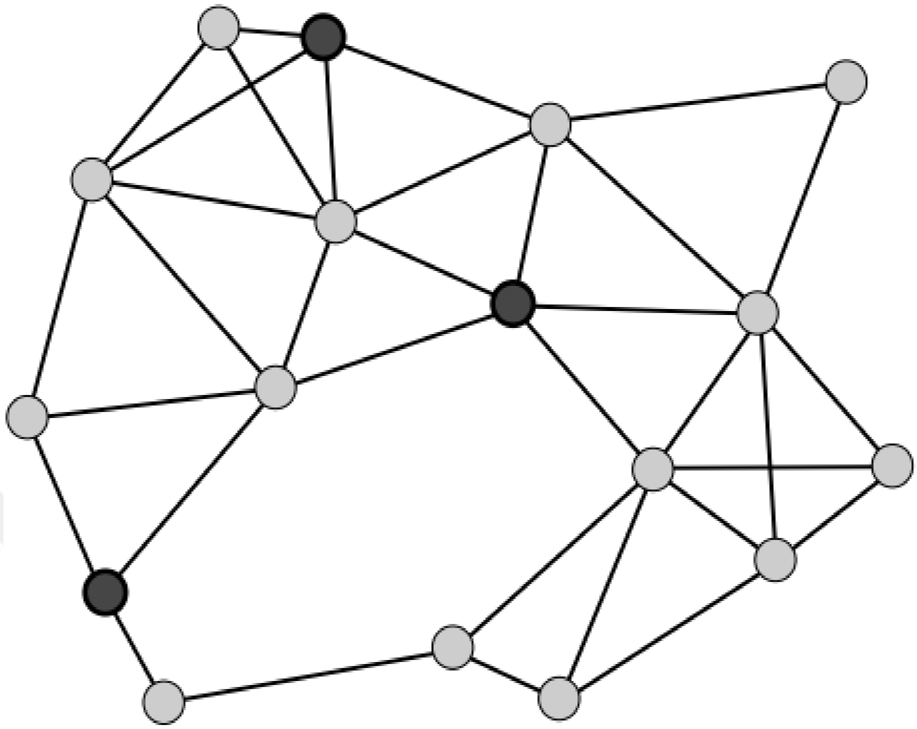

Figure 1.2: The localization problem as finding the locations of the unknown points (lighter) given the locations of a few known points (darker)

1.3 CONTRIBUTIONS OF THESIS

The main contribution of this message is the use of a new approach (SSA) to locate some unknown points in the area of sensor networks based on the idea of jellyfish. A comparative study of some key algorithms such as PSO and BOA in this field has been conducted with this method to measure their efficiency. The results showed that this method is better in terms of accuracy and speed and less error rate compared to other methods of the same field and to address the same problem.

1.4 THESIS STRUCTURE

We held the rest of thesis as follows:

- Chapter 2 Illustrate background of heuristic optimization algorithms.
- Chapter 3 Reviews some of the previous works of the researchers in the same field, which developed this area.
- Chapter 4 Provides a detailed description for the proposed method.
- Chapter 5 Provides several experiments that have been implemented to evaluate the proposed method.
- Finally, Chapter 6 Presents the conclusion.

2. BACKGROUND

This chapter presents brief description for all the concepts that necessary to understand the proposed work. It starts with presenting an overview on Meta-Heuristic optimization. Then, Meta-Heuristic Algorithms for WSN Localization are overviewed. Finally, the chapter is concluded by explain the main idea behind the localization algorithms.

2.1 OVERVIEW OF META HEURISTIC OPTIMIZATION ALGORITHMS

Over the past years, many natural-inspired methods have been discovered to detect unknown spots through some known points. Through these methods, many algorithms have been proposed and improved, and older ones have been improved. Modern materials based on nature-inspired methods rely on dynamic methods and methods and are implemented automatically to solve many problems. Modern algorithms have a good and effective performance in solving harmonic and nonlinear problems. Given the importance of this area and its wide scope in the field of research and application, the area of research is constantly increasing in solving the problems related to it and applying many of the most flexible and capable algorithms to overcome many constraints. Scientists and researchers in this field have been able to link nature with the methods inspired by the way animals and insects are detected for food, the problems of determining the sensors and how to identify unknown points through unknown points [5].

According to Voss et al. [7], a meta-heuristic is: "The process of subordinate reasoning to know and produce good, high quality and efficient solutions is a fundamental and repetitive process. Good solutions are not good enough unless they are repeatable and improved by repetition. In the beginning, the solution is not good and unsatisfactory, but over time it can be a complete solution. The subordinate reasoning may consist of high-level procedures and processes."

Random distribution often achieves a wide range of diverse solutions. One of these solutions is meta-reasoning. Although meta-heuristics is not an agreed definition and is widely used by researchers, they agreed to name all the algorithms that deal with randomness and to identify randomized locations with a metaheuristic [7].

Metaheuristic algorithms are further classified into: Trajectory methods and Population-based methods. There are many methods and many terms and methods different from research methods and research space. Among these methods is the path method and this method is characterized by it working on one solution. It also offers different properties in the treatment and is characterized by its strength and performance. Simulations and random adaptive actions are examples of pathways. SA, TS, and GRASP are instances for Trajectory methods [8].

On the other side, in population-based methods, meta-heuristics explicitly work with a set of solution. Another kind of inference is the aggregate inference which often uses population characteristics to guide research. These inferences are based on the development and improvement of the body swarm. Another category of meta-inference is the leprechaun intelligence, a collective behavior of self-regulating decentralized factors in a society or a squadron. Examples of this class are improved particle swarm, salp swarm, bee colony algorithms, and improved butterflies [8].

Metabolic inferences, which are used by many organisms such as butterflies, bees, ants, wolves and others. These inferences have been found by discovering many ways for these organisms to search for food in the shortest time and shortest distance. These methods also depend on collective and decentralized behavior.

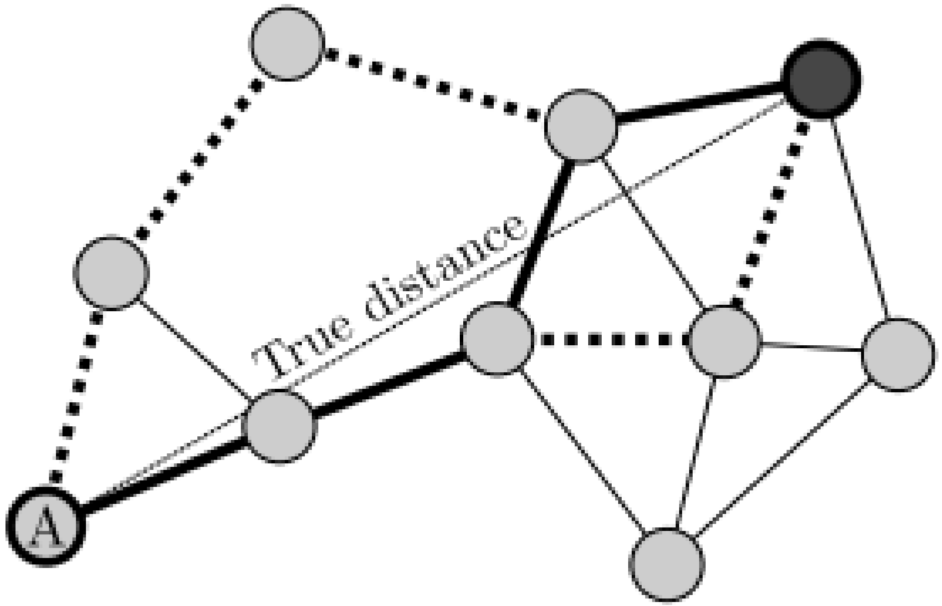

Figure 2.1: Distance Path between Two Nodes [9]

As displayed in figure (2.1), we need to determine the distance between point A and the dark slope. Distance can be measured in several different ways and in many paths. The best path can be the Luxor and referred to as the thick path. The Luxor track is the shortest in terms of hops. When errors occur, the shorter path will be inaccurate. This is why there are many solutions represented in many available tracks and not always the shortest path is the best possible long - distance caller and that has many active sensors. With many paths available, opportunities are increasing with the number of potential routes that one will severely reduce. [9].

2.1.1 Particle Swarm Optimization (PSO)

It is like a flock of birds, which also acts as swarms and fish, where each individual learns from his or her own experiences and from the rest of the herd. This algorithm provides several possible solutions within the search area. The randomized particle sampler is evaluated in terms of proximity to the rest of the known squadron [10].

These scraps travel in exploration space serving practices motivated by bird flocking ways to obtain distinct places with higher fitness. The PSO method applies a set of possible clarifications called 'particles' that are populated in the exploration space with arbitrary primary positions. The conditions of the proper role corresponding to the particle locations are estimated. Then the scraps are relocated in the exploration space serving practices excited bird flocking style. Each scrap is transferred towards a randomly weighted average of the most excellent location [10].

Algorithm 3 Pseudo code of Particle Swarm Optimization (PSO) algorithm

```
Objective Function f (X), X= (x1, x2,…xd)
Generate initial population of n particles, Xi,i =1,2,.,n
while (t< MaxGeneration)
for each particle
    Calculate fitness value
     Update best fitness value (pBest) in history
      Set current value as the new pBest
  end for
 Choose the particle with the best fitness value as gBest
  for each particle
      Calculate particle velocity
      Update particle position
  end for
end while
Post-process the results
```

Figure 2.2: Pseudo Code of PSO [10]

2.1.2 Butterfly Optimization Algorithm (BOA)

BOA method is a novel nature-inspired positioning method produced by Arora [11]. It depends on the food foraging approach. Butterflies apply insight natural chemoreceptors to determine the origin of their meat/food. Specific chemoreceptors, can sense perfume and are spread whole body sections. In BOA, certain butterflies are the exploration operators who control optimization.

This algorithm assumes that some butterflies emit a distinctive smell that can be sensed and inhaled by other butterflies. Some of these butterflies improve research, to find other places to eat. Every place has a fragrance that distinguishes it if the fragrance is changed, that is, the place has been changed. [11]. Depending on the natural performance of the butterflies, the butterfly, if inhaled or sensed by some fragrance or distinctive smell of other butterflies, is conclusive evidence of their presence and presence of food and then directed to them. This method works on the path inspired by the butterflies to know unknown places in relation to a known place. In different situation, once a butterfly is cannot smell fragrance bigger than its perfume, it will run arbitrarily, and this condition is called as the limited exploration stage. The principal energy of BOA rests in its tool to change perfume in the method. To learn the intonation, first, it should be reflected that how a provocation of an real organism processes any smell like sound, aroma, warmth, daytime. The entire notion of sensing and concocting the modality is based on three critical relations such as provocation strength, representative power and modality. Modality is a notion described to estimating the model of power and concocting it. Provocation magnitude is the measure of the natural/actual provocation.

Algorithm 1 Pseudo code of the Butterfly Optimization Algorithm (BOA)

```
Objective function f(x), x=(x_1 ……x_dim)
Generate population of n Butterflies x_i= (i=1,2,…n)
Define c, a and p
while stopping criteria not met do
    for each butterfly bf in population do
        Calculate fragrance for bf
    end for
    Find the best bf
    for each butterfly bf in population do
        Generate a random number r from [0, 1]
        if r < p then
            Move towards best butterfly
        else
            Move randomly
        end if
    end for
end while
Output the best solution found.
```

Figure 2.3: Pseudo Code of BOA [11]

2.1.3 Salp Swarm Algorithm (SSA)

Salps are a member of the family salp with a clear roller form shape. Seem they such as jellyfishes in character and action. The water is propelled salps groups to improve. Salp -swarm approach was the principal motivation to make Salp- Swarm- Algorithm [12].

Salp make the swarm at deep oceans; this colony named salp series. The problem of salps swarm's performance is not well represented yet. However, some researchers examine such procedure has been done to enhance their action in attempting for food. Initially, the salps community has been separated into two associations: head and members to express salp chains[12].

Furthermore, Similar to other swarm-based procedures, the location of salps is defined in an n-dimensional exploration area where n is the amount of variables of an assigned dilemma. Accordingly, the location of all salps is collected in a two-dimensional matrix named x. It is also believed that there is a food reference named F in the exploration area as the swarm's destination. To renew the attitude of the master the following equation is introduced [12]:

$$x_j^1 = \begin{cases} F_j + c_1\left((ub_j - lb_j)c_2 + lb_j\right) & c_3 \geq 0 \\ F_j - c_1\left((ub_j - lb_j)c_2 + lb_j\right) & c_3 < 0 \end{cases} \tag{2.1}$$

where x_j^1 determines the location of the primary salp (leader) in the j^{th} dimension, F_j is the location of the feed origin in the j^{th} dimension, ub_j designates the upper bound of j^{th} dimension, lb_j designates the lower bound of jth dimension, c_1 , c_2 , and c_3 are arbitrary integers. Eq. (1) determines that the leader only renews its position with respect to the feed origin[12]:

$$c_1 = 2e^{-\left(\frac{4l}{L}\right)^2} \tag{2.2}$$

$$x_j^i = \frac{1}{2}\left(x_j^i + x_j^{i-1}\right) \tag{2.3}$$

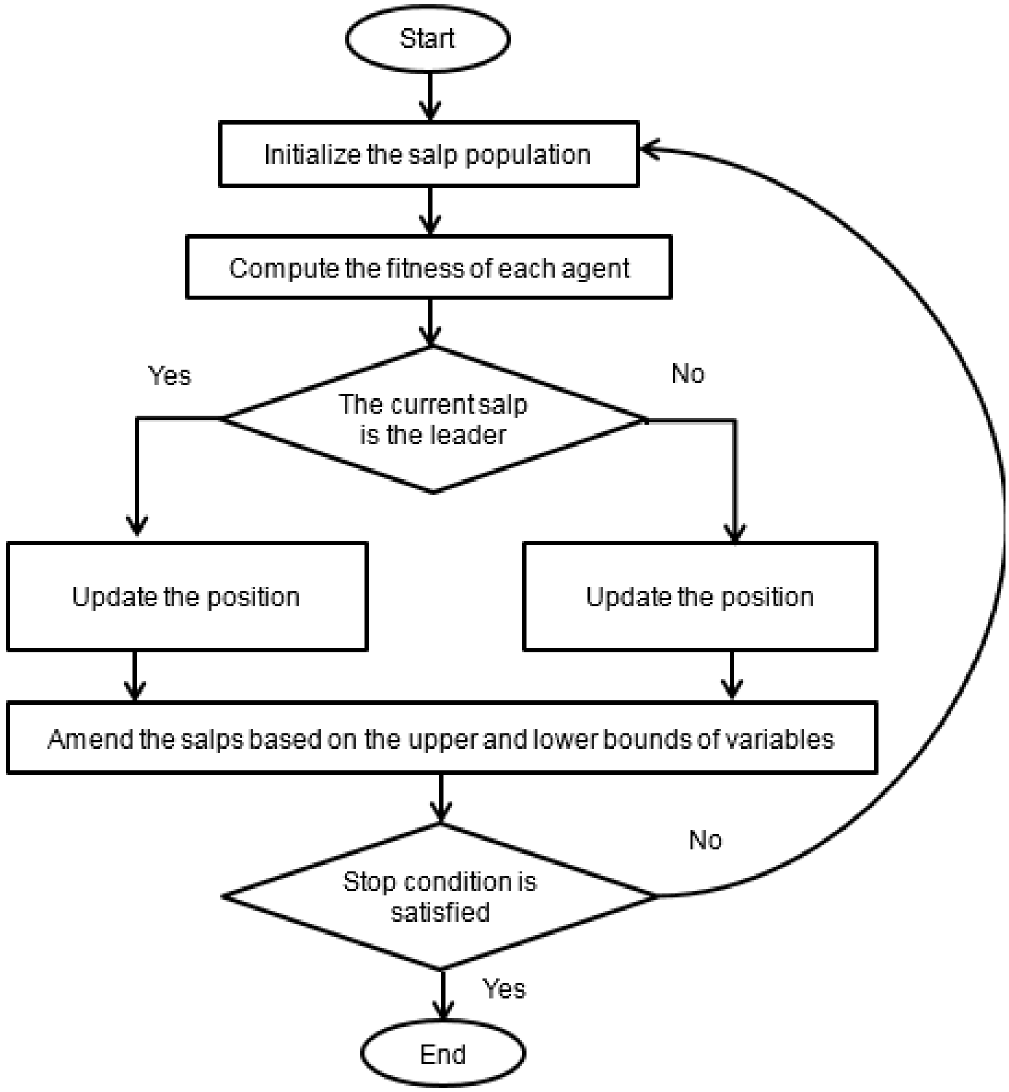

Figure 2.4: Flow chart of SSA [12]

2.1.4 Firefly Algorithm

FA is a nature-inspired method which simulates the familiar presence of fireflies located in the hot country [13]. Fireflies perform several types of flashing patterns to communicate, search and discover their mating companion. Yang admired these flashing points of fireflies to produce a FA-inspired method. In FA, three laws were idealized, which are:

- All the fireflies are considered as unisexual by which any firefly can become interested in various firefly present in the neighboring, irrespective of their gender.
- The affinity of various firefly are immediately proportionate into they glimmering. It suggests each firefly with less shine will influence proceeding that butterfly which represents more shine.
- The brightness of a firefly is measured using the accurate purpose

The principal method of FA is concentrated on two primary problems, i.e., how the light concentration is to be mixed and how the tendency is expressed. For carelessness, the attractiveness of several fireflies is measured by its illumination which is extra associated with the defined purpose function [13].

2.1.5 Bat Algorithm

A novel meta-heuristic approach called bat method [14] based on the echolocation operation of bats. BA produced to utilize the benefit of living approaches and other exciting discoveries excited by the extreme function of echolocation of microbats. BA is much higher to several existing methods in phases of efficiency and productivity. The dilemma in accuracy rate is minimal because of the bat cannot find all way in the exploration space.

1. Objective function $f(x), x = (x_1, \dots \dots \dots x_d)^T$
2. Initialize the bat population $x_i(i = 1,2,3 \dots\dots n) and\ v_i$
3. Define Pulse frequency $f_i\ at\ x_{i.}$
4. Initialize the rates r_i and the loudness A_i
5. While (t< Max number of iterations)
6. Generate new solutions by adjusting frequency and updating velocities and locations
7. If $(rand > r_i)$
8. Select a solution among the best solutions
9. Generate a local solution around the selected best solution
10. End if
11. Generate a new solution by flying randomly
12. If $(rand < A_i)\&f(x_i < f(x^*))$
13. Accept the new solutions
14. Increase r_i and reduce A_i
15. End if
16. Rank the bats and find the current best x^*
17. End while

Figure 2.5: Steps of BA [14]

2.1.6 Grey Wolf Optimization

GWO is a inspired method suggested by Mirjalili et al. in 2014 that focuses on social performance of wolves [15]. This algorithm is inspired from grey wolves that belong to canidae family. It simulates the leadership quality and the hunting behaviour of grey wolves in three steps as tracking, encircling and attacking. Grey wolves consists of 5-12 wolves. Grey wolves live in pack that contains 5-12 wolves. α, β, δ and ω are four types of grey wolves following a strict social hierarchy. α is the dominant wolf among the other grey wolves that makes different decisions which are followed by other submissive grey wolves. β grey wolf is second in the hierarchy after α grey wolf. β grey wolf help the dominant leader α to make decisions about sleeping etc.

```
Initialize the population of grey wolves x_i , (i=1,2,3….n)
Initialize a, A and C
Calculate the fitness of each search agent or wolf
X_α=the best search agent
X_β=the second best search agent
X_δ=the third best search agent
  while (t < Max number of iterations)
      for each search agent
       Update the position of current search agent
       end for
     Update a, A and  C
     Calculate the fitness of all search agents.
     Update X_α, X_β, X_δ
  end while
  return X_α
```

Figure 2.6: Pseudo Code of GWO [15]

2.2 COMPARATIVE STUDY OF META-HEURISTIC ALGORITHMS FOR WSN LOCALIZATION

In the following table we have listed a set of previous works that are similar to our work and some of their findings. In 2008, some researchers used the BSO algorithm and reached a precision of 77 percent. But in the years 2011 to 2016 researchers used other algorithms to achieve more accurate results and reduce the error rate.

Table 2.1: Comparison Among Various Localization Methods

Year	Objective	Localization Technique	Algorithm	Accuracy
2008	WSN Localization	Anchor Based Range Based	Practical Swarm Optimization (PSO)	Too many result Localization Error = 23%
2011	WSN Localization	Anchor Based Range Based	Hybrid DV distance and Practical Swarm Optimization (PSO)	Localization Error = 12%
2013	WSN Localization	Anchor Based Range Based	Hybrid Bacterial foraging optimization (BFO) and Practical Swarm Optimization (PSO)	Mean localization Error = 0.47
2013	WSN Localization	Anchor Based Range Based	Genetic Algorithm (GA)	Too many result Localization Error = 15%
2015	WSN Localization	Anchor Based Range Based	Butterfly Optimization Algorithm	Localization Error = 8%
2016	WSN Localization	Anchor Based Range Based	Genetic Algorithm (GA) and Practical Swarm Optimization (PSO)	Too many results in many scenarios

3. RELATED WORKS

3.1 INTRODUCTION

This chapter reviews a some of previous works in this area. As well as a simplified list of each work and the contents of the algorithms and measurements reached.

3.2 PREVIOUS WORKS

In a sensor network, there will be a large number of sensor nodes densely deployed at positions which may not be predetermined. In most sensor network applications, the information gathered by these micro-sensors will be meaningless unless the location from where the information is obtained is known. This makes localization capabilities highly desirable in sensor networks [2]. Theoretically, a localization measurement device such as global positioning system (GPS) can be used for a sensor to locate itself. However, it is not practical to use GPS in every sensor node because a sensor network consists of thousands of nodes and GPS will be very costly. On the other hand, GPS does not work at all in indoor environments, so alternative solutions must be employed [3].

To solve the problem, many localization methods have been developed. Instead of requiring every node to have GPS installed, all localization methods assume only a few nodes be equipped with GPS hardware. These nodes are often called anchor nodes and they know their positions. Other normal sensors can communicate with a few nearby sensors and estimate distances between them using some localization algorithm [e.g. received signal strength (RSS), time of arrival (ToA)] and then derive their positions based on the distances [4].

WSN is treated as multi-model and multidimensional optimization problem and addressed through population based stochastic techniques. A few genetic algorithm (GA) based node localization algorithms are presented in that estimate optimal node locations of all one-hop neighbors. A two phase centralized localization scheme that uses simulated annealing (SA) Algorithm and GA is presented in [7]. Particle swarm optimization (PSO) based algorithm is proposed in [4, 8], to minimize the localization error.

In [5], they have introduced a new method that is correctly finding the location of target nodes while reducing their energy loss and storage conditions. The recommended method divides the job of localization between target nodes and the central station and does not require the behavior of several support nodes (nodes with known positions). It suggests setting the known nodes in a circle or a semi-circle around the edge of the WSN. Not only this positioning approach leads to more reliable localization, but also it is also very suitable for WSNs used for environmental monitoring, military direction, or tracking purposes. The accuracy of the recommended procedure was assessed and correlated to other peer methods using the simulator (NS). Outcomes determine that important improvement is achieved with the recommended approach when containing metrics such as power and localization failure while varying other simulation factors such as the amount of target nodes and the space size.

In [14], the meta-heuristic optimization method identified as bat algorithm is defined to estimate the correctness of node localization difficulty in wireless sensor networks. Meanwhile, the existing bat algorithm has also been changed by using the bacterial foraging procedures of bacterial foraging optimization method. Compared with the current bat method, the introduced modified bat algorithm is shown within simulations to achieve consistently better not only in improving localization success ratios and fast confluence speed but also improve its robustness.

In [16], the main objective of this research is to discover and locate nodes by two purses and PSO and another method inspired by the discovery of bees for its food and known as artificial bees. This study compares these two methods with other sets of algorithms used in this field. In this study it was found that this combination proved its efficiency in determining the distant nodes with high precision and a small line ratio compared to other systems in the same field.

In [17], they have given a new localization procedure that merges the collected signal strength indicator approach which defines the connections between nodes to the range of an available radiated signal, with a distinct trend which is social network interpretation that deals with associations between nodes in any network with metrics and layouts. By using combined parameter between degree and closeness, they will keep the fitting selected roots that will be anchors for around nodes inside the network. Trilateration predictions will be applied between optimized picked nodes with higher centrality to localize the target nodes.

In [18], Grey Wolf Optimization (GWO) method is combined to spot the accurate location of undiscovered nodes, to handle the node localization dilemma. The recommended task is performed utilizing MATLAB application whereas target nodes are expanded in an arbitrary location inside the aspired chain region. The factors like evaluation performance time, a number of the positioned node, and smallest estimation error calculations are employed to examine GWO rule.

In [19], [20], they have introduced a two-objective memetic strategy called the Three Phase Memetic procedure that determines the positions of sensor nodes with high precision. The recommended method is formed of three operators (phases). The first stage, which is a mixture of three node-estimating procedures, is handled to produce good starting positions for sensor nodes. The secondary and third stages are then employed for decreasing the localization failures in the first operator.

In [21], the principles and practice of failures in Angle of Arrival (AOA) and Received signal strength indicator (RSSI) localization procedures have been mathematically examined. Based on the failure investigation of both the current methods, a hybrid localization method is introduced. The hybrid localization method is based on current AOA and RSSI.

In [4], they have proposed a distributed approach for localization, namely, Multidimensional Scaling with refinement using trilateration (MDS-DRT). The algorithm has been analyzed for varying number of node densities, number of anchors, and radio ranges. The simulation results show that the proposed algorithm performs better than the existing algorithms in terms of accuracy with reduced computational complexity.

4. PROPOSED METHODOLOGY

4.1 INTRODUCTION

The objective of sensor node localization using nature inspired algorithms is to evaluate the position of the maximum number of target nodes using analytical information about the position of anchor nodes. SN localization dilemma expresses using the unique hop range-based allocation procedure to evaluate the location of the unknown node coordinates (X, Y) with the aid of anchor nodes (position of known nodes) coordinates (x, y). To estimate the coordinates of N unknown nodes, the scheme followed is given below in Figure. (4.1).

ALGORITHM: Target Node Localization using Anchor Nodes

INPUT: N (unknown nodes), M (anchor nodes), R (communication range)

OUTPUT: localized nodes (N_L) and Localization Error

Step 1: Randomly Initialize the N unknown nodes and M anchor nodes within the communication range (R). Anchor nodes measure their position and communicate their coordinates to their neighbors. For all iterations, the node which settles at the end is termed as reference node and this node will act as anchor node.

Step 2: Three or more anchor nodes within the communication range of a node are considered as localized node.

Step 3: Let (x, y) be the coordinates of the target node to be determined and d_i be the distance between the target node and the i^{th} anchor node.

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \qquad (5)$$

Step 4: The optimization problem is formulated to minimize the error of localization problem. The objective function for the localization problem is formulated as:

$$f(x, y) = \min \left(\sum_{i=1}^{M} \left(\sqrt{(x - x_i)^2 + (y - y_i)^2} \right)^2 \right) \qquad (6)$$

where M is the anchor nodes within the transmission range (R) of the target node.

Step 5: All target localized nodes (N_L) are determined, the whole localization error is calculated as the mean of square of distances of the estimated coordinates node (x_i, y_i) and the actual node coordinates (X_i, Y_i), for i = 1, 2, . . . , N_L

$$E_L = \frac{1}{N_L} \sum_{i=1}^{L} \left(\sqrt{(x_i - X_i)^2 + (y_i - Y_i)^2} \right) \qquad (7)$$

The performance of SSA algorithm evaluated using E_L and the number of non-localized nodes N_{NL}, where $N_{NL} = [N - N_L]$.

Step 6: Repeat the steps 2–5 until all unknown/target nodes get localized or no more nodes can be localized.

Figure 4.1: Steps of Localization using Proposed Inspired Algorithm.

4.2 METHDOLOGY FLOWCHART

Anchor nodes are stationarity located. Most of the nodes in the WSN are not implemented with GPS due to high cost. The localization problem can be formulated as an objective function which is to be minimized using nature inspired algorithm. The overall flowchart of range based distributed localization of sensor nodes using nature inspired algorithm is shown in Figure. (4.2).

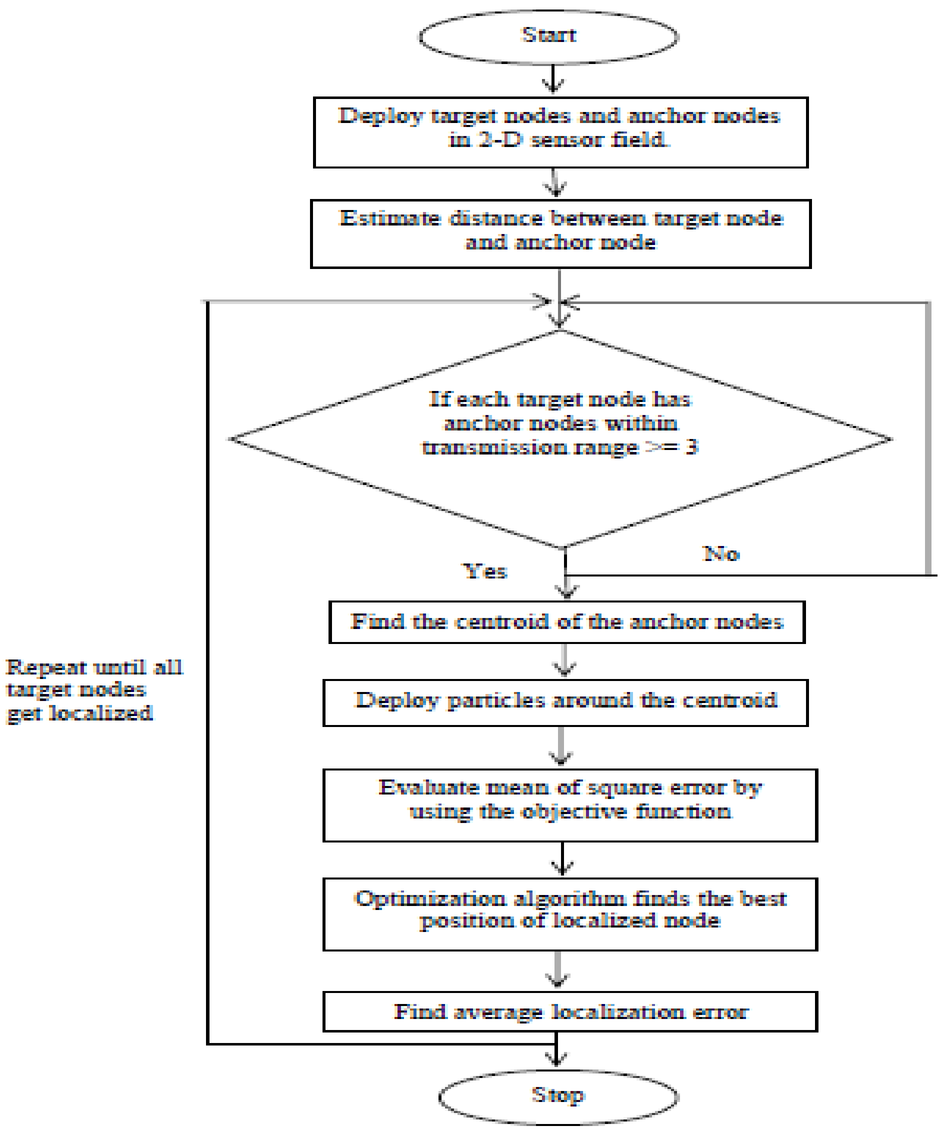

Figure 4.2: Flow Chart of Sensor Node Localization using Proposed Inspired Algorithm

4.3 IMPLEMENTATION SCREENSHOTS

```
%Initalization
an = 7;  %number of anchor sesnor nodes (known position)
tn = 25;  %number of target sensor nodes (Target node)
network_area = 100; %size 100*100
Iterations = 100; %iteration numbers

anchors   = [0 0; network_area 0;0 network_area; network_area network_area; 50 50;
             10 10 ; 90 90]; %determine anchor nodes position
target_nodes  = network_area*rand(tn,2); %random location

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

Figure 4.3: Deploy Objective Nodes and Reporter Nodes in 2D Space

In figure above, we display a piece of code developed in MATLAB to create a random position of objective points that called target nodes. These total number of nodes in this experiment is 25. Also, initialize the locations of reporter nodes (anchor nodes) with maximum 100 iterations.

```
f1 = figure(1);
clf
plot(anchors(:,1),anchors(:,2),'ks','MarkerSize',5,'lineWidth',2,'MarkerFaceColor','k');
grid on
hold on
plot(target_nodes(:,1),target_nodes(:,2),'ro','MarkerSize',5,'lineWidth',2);
distance = zeros(an,tn);
for m = 1 : tn
    for n = 1 : an
        distance(n,m) = sqrt( (anchors(n,1)-target_nodes(m,1)).^2 + ...
                              (anchors(n,2)-target_nodes(m,2)).^2  );
    end
end
```

Figure 4.4: Calculate Distance Between Target Nodes and Anchor Nodes

In figure above, we display a piece of code to plot the points in area 100*100. Then, we create a nested for LOOP to calculate distances between these points.

```
tic; %start_time

[SSA_Best_scores,SSA_Best_poss,SSA_Errr,SSA_NL,SSA_T]=SSA(25,100,10,50,10,0.04,24,0.3,estimationDistance);

for m = 1 : tn
    for t = 1 : Iterations

        estimationDistance   = sqrt(sum( (anchors - repmat(estimationNode(m,:),an,1)).^2 , 2));

        R   = [(estimationNode(m,1)-anchors(:,1))./estimationDistance ... % x-coordinate
                 (estimationNode(m,2)-anchors(:,2))./estimationDistance];   % y-coordinate

        weight = - (R.'*R)^-1*R.' * (estimationDistance - noise(:,m));
        % Updating the estimation
        estimationNode(m,:) = estimationNode(m,:) + weight.';

    end
end
elapsed = toc; %end_time
```

Figure 4.5: SSA Implementation and Time Calculation

In figure above, we display a piece of code to calculate time and estimation distance of proposed SSA approach between reporter points and target points.

```
%Draw result for localization
plot(estimationNode(:,1),estimationNode(:,2),'gs','MarkerSize',5,'lineWidth',2);
legend('Anchor locations','Target location','Node estimated location',...
          'Location','Best')

%Calculate Mean Estimation error
Err = mean(sqrt(sum((estimationNode-target_nodes).^2)));
title({'\fontsize{20} {\color{black} Proposed Result with It. 100}';['\fontsize{12}
axis([-0.1 1.1 -0.1 1.1]*network_area)
```

Figure 4.6: Accuracy and Error Calculation

5. EXPERIMENTAL RESULT

5.1 EXPERIMENTAL PARAMETERS

In this section, the proposed WSN localization approach is evaluated under different scenarios. Also, the proposed algorithm performance is compared to two other particle swarm optimization (PSO) and butterfly optimization algorithm (BOA) in terms of localization accuracy and computing time. All the calculations of the three algorithms (SSA, PSO, and BOA) are executed in MATLAB R2012b using a machine of Intel Core i7 CPU, 4GB RAM, and Windows7 operating system. The parameter values of the deployment area are shown in Table 2.

Table 5.1: Factors Setting of Simulation Environment

Parameters	**Values**
Sensor nodes	Varies on $\sum_{i=1}^{4} i * 2\,5$
Anchor nodes	Varies on $sensor\ nodes/4$
Node transmission range (R)	30 m
Deployment area	100 m*100 m
Number of iterations	100

5.2 ATTRIBUTES THAT EFFECT LOCALIZATION ACCURACY

5.2.1 Effect of Anchor Node Density

In order to improve the efficiency of the invisible nodes positioning system, the fixed nodes must be increased. The accuracy of the algorithms and the error ratio in the determination of places depend on the number of fixed nodes and the area of coverage for each node. The percentage of the correct expectation of the unknown location by the number of nodes depends on the size and number of nodes known as shown in Table 5.2.

5.2.2 Effect of Number Of Iterations

The improvement in the number of repetitions assists in localizing a higher number of nodes as shown in table 5.2. On the other hand, if a node has more references in iteration k + 1 than in iteration k, the time required for localization increases.

5.3 COMPARATIVE STUDY BETWEEN PROPOSED AND OTHER LOCALIZATION ALGORITHMS

In this section, the accuracy of the recommended SSA based localization algorithm is analyzed to the performance of two other well-known optimization algorithms, namely PSO and BOA. The performance of the different localization algorithms is evaluated using several performance metrics including Mean Localization Error (EL) in meters, Computing Time in seconds, and number of localized nodes (NL). The experimental results of the different localization algorithms are shown in Table 5.2.

Table 5.2: Experimental Results of the Different Localization Algorithms

Target Nodes	Anchor Nodes	PSO			BOA			Proposed		
		E_L(m)	T(s)	N_L	E_L(m)	T(s)	N_L	E_L(m)	T(s)	N_L
25	**7**	0.25	0.4	19	0.1	0.3	22	**0.04**	**0.3**	**24**
50	**13**	0.08	0.7	46	0.02	0.6	49	**0.001**	**0.5**	**50**
75	**19**	0.04	0.9	72	0.01	0.8	74	**0.001**	**0.6**	**75**
100	**25**	0.1	1.3	91	0.05	0.9	95	**0.01**	**0.7**	**99**

5.4 SCREEN SHOTS OF RESULTS

5.4.1 Results of Seven Anchors And Twenty-Five Target Nodes

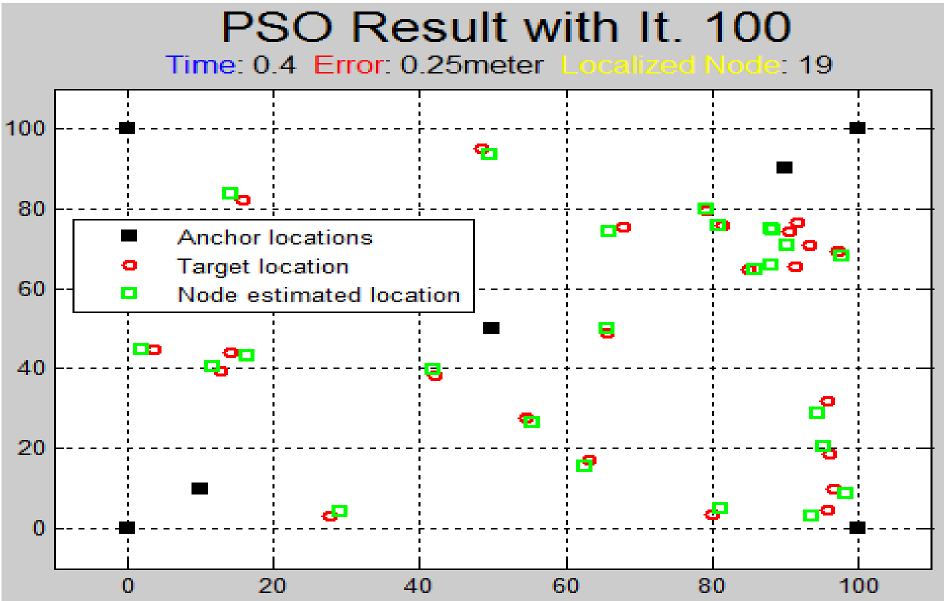

Figure 5.1: Experiment 1 of PSO Results with 7 Reporters and *25* Objectives Nodes

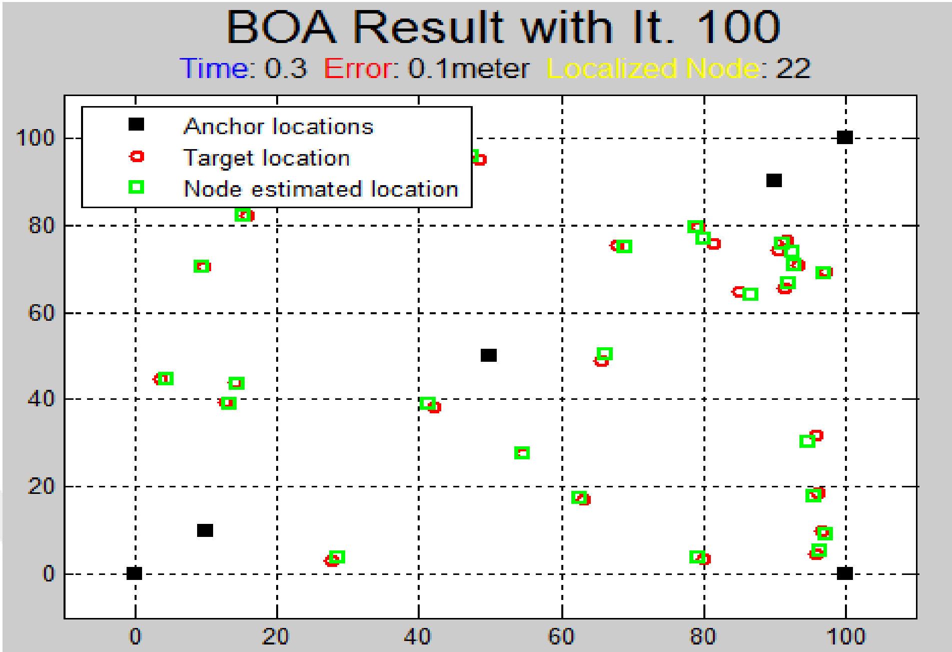

Figure 5.2: Experiment 1 of BOA Results with 7 Reporters and *25* Objectives Nodes

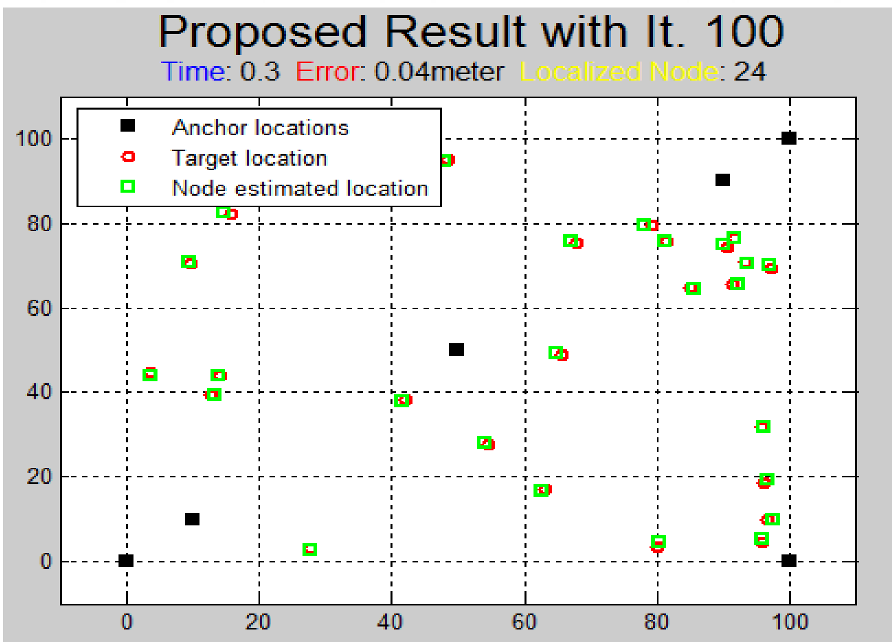

Figure 5.3: Experiment 1 of Proposed Method Results with 7 Reporters and *25* Objectives Nodes

In the previous experiment (first experiment) we used a simulation program for a 100-meter length and 100-meter-width display of 25 unknown nodes in a randomized manner and 7 of the anchor nodes are fixed and known position. We also compared three algorithms in several attempts. We noticed several observations, the proposed system achieved best results in time and a small error percentage compared to the rest of the systems. Where the proposed system achieved 0.04 error ratio at 0.3 seconds.

5.4.2 Results of Thirteen Anchors And Fifty Target Nodes

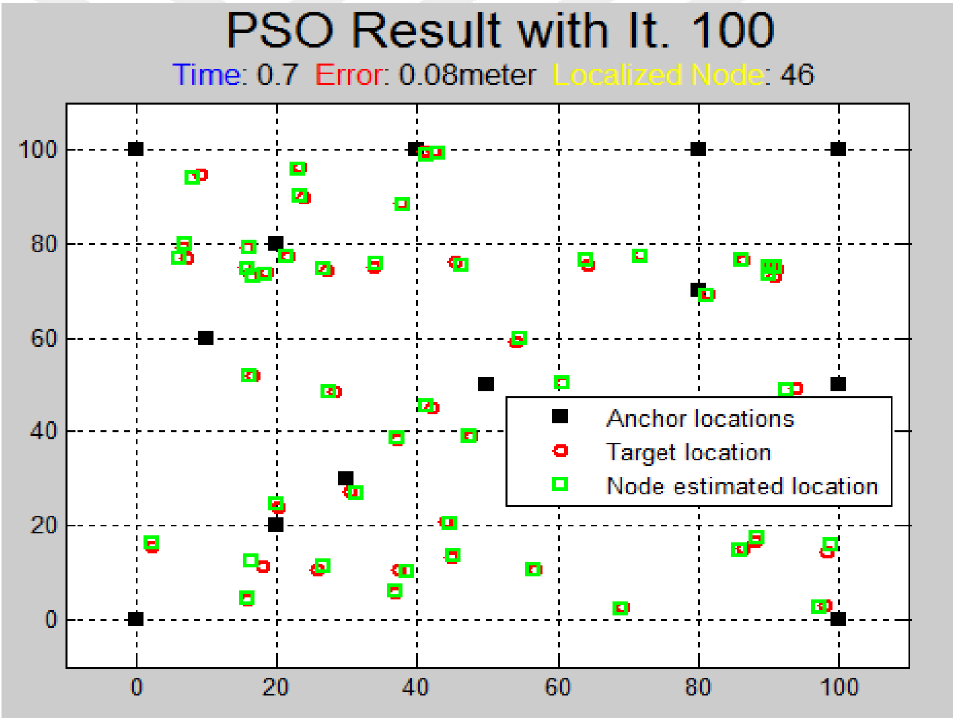

Figure 5.4: Experiment 2 of PSO Results with 13 Reporters and 50 Objectives Nodes

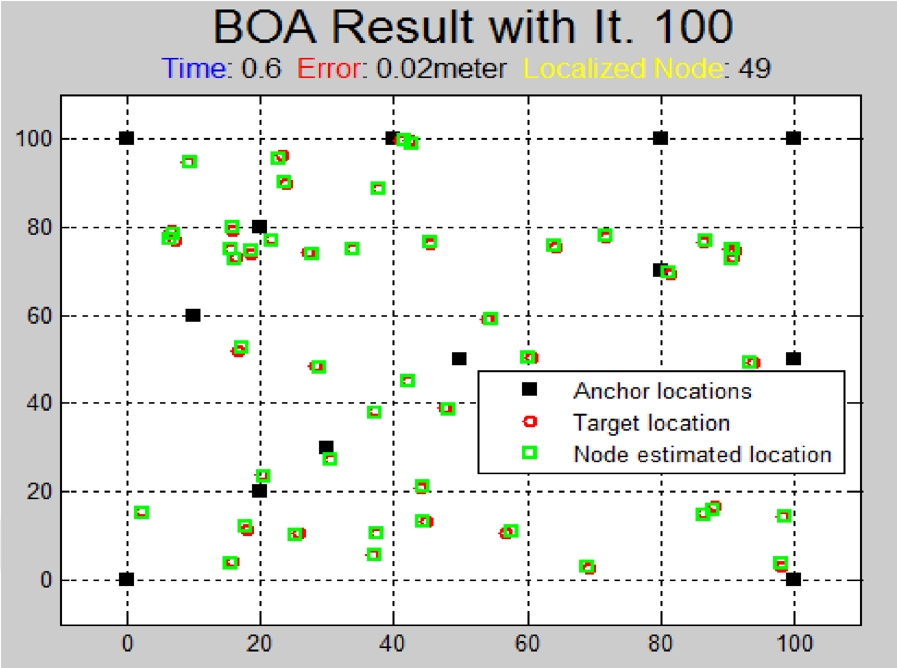

Figure 5.5: Experiment 2 of BOA Results with 13 Reporters and 50 Objectives Nodes

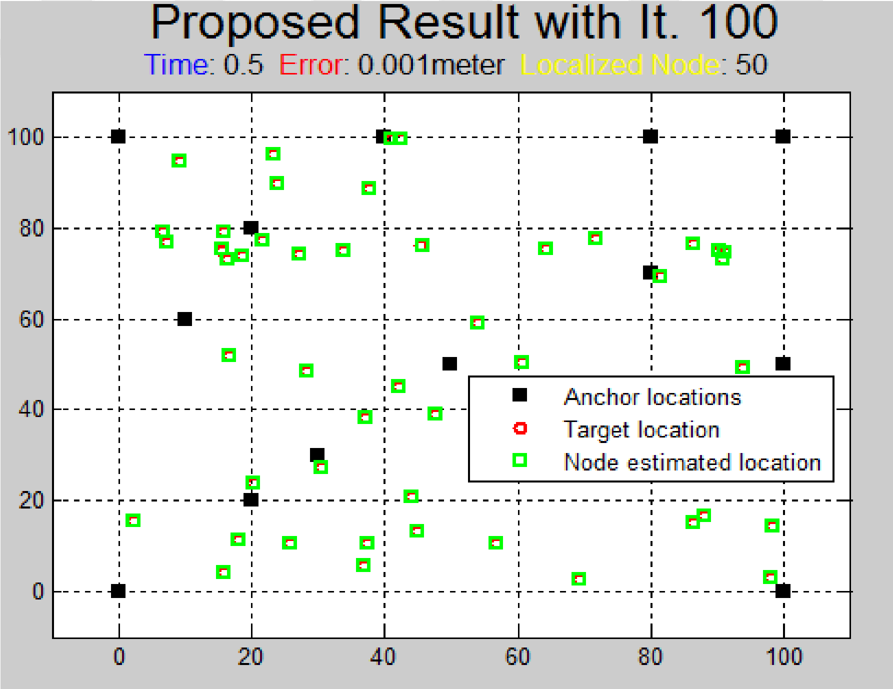

Figure 5.6: Experiment 2 of Proposed Method Results with 13 Reporters and 50 Objectives Nodes

In the previous experiment (second experiment) we used a simulation program for a 100-meter length and 100-meter-width display of 50 unknown nodes in a randomized manner and 13 of the anchor nodes are fixed and known position. We also compared three algorithms in several attempts. We noticed several observations, the proposed system achieved best results in time and a small error percentage compared to the rest of the systems. Where the proposed system achieved 0.001 error ratio at 0.5 seconds.

5.4.3 Results of Nineteen Anchors And Seventy-Five Target Nodes

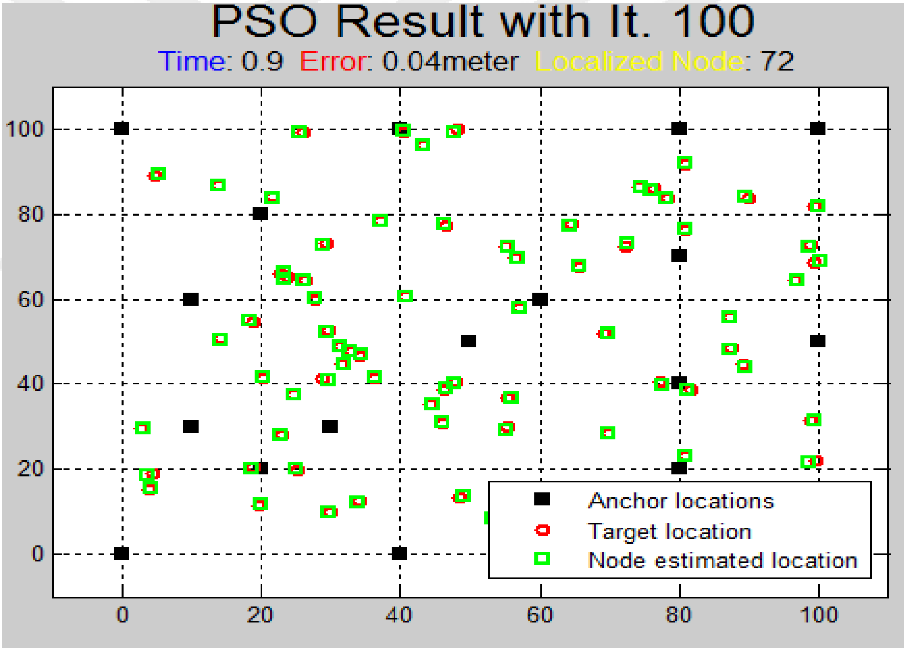

Figure 5.7: Experiment 3 of PSO Results with 19 Reporters and 75 Objectives Nodes

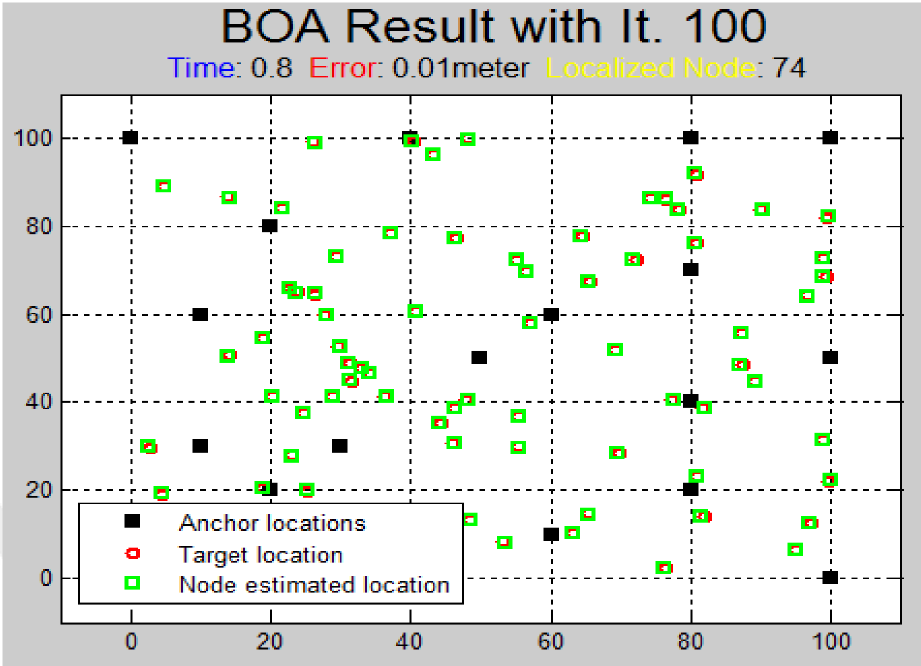

Figure 5.8: Experiment 3 of BOA Results with 19 Reporters and 75 Objectives Nodes

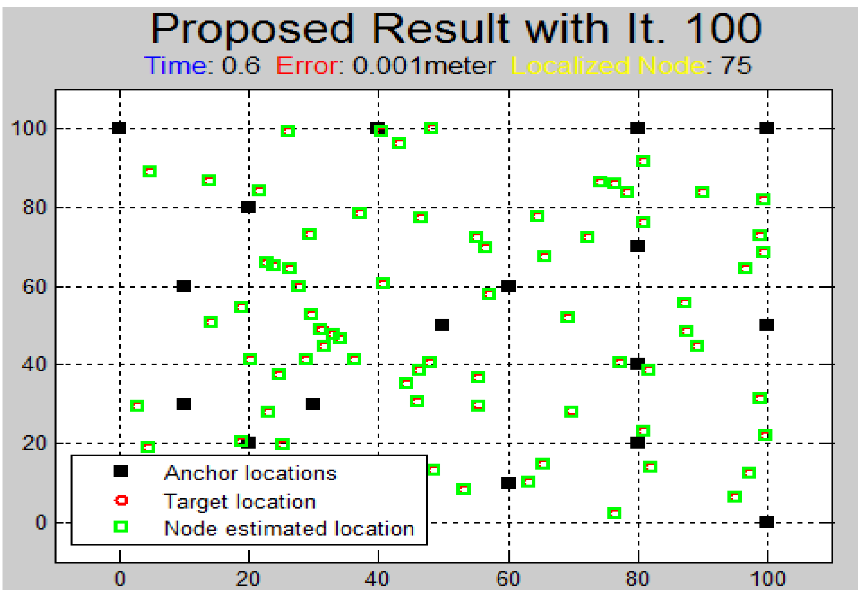

Figure 5.9: Experiment 3 of Proposed Method Results with 19 Reporters and 75 Objectives Nodes

In the previous experiment (third experiment) we used a simulation program for a 100-meter length and 100-meter-width display of 75 unknown nodes in a randomized manner and 19 of the anchor nodes are fixed and known position. We also compared three algorithms in several attempts. We noticed several observations, the proposed system achieved best results in time and a small error percentage compared to the rest of the systems. Where the proposed system achieved 0.001 error ratio at 0.6 seconds.

5.4.4 Results of Twenty-Five Anchors And One-Hundred Target Nodes

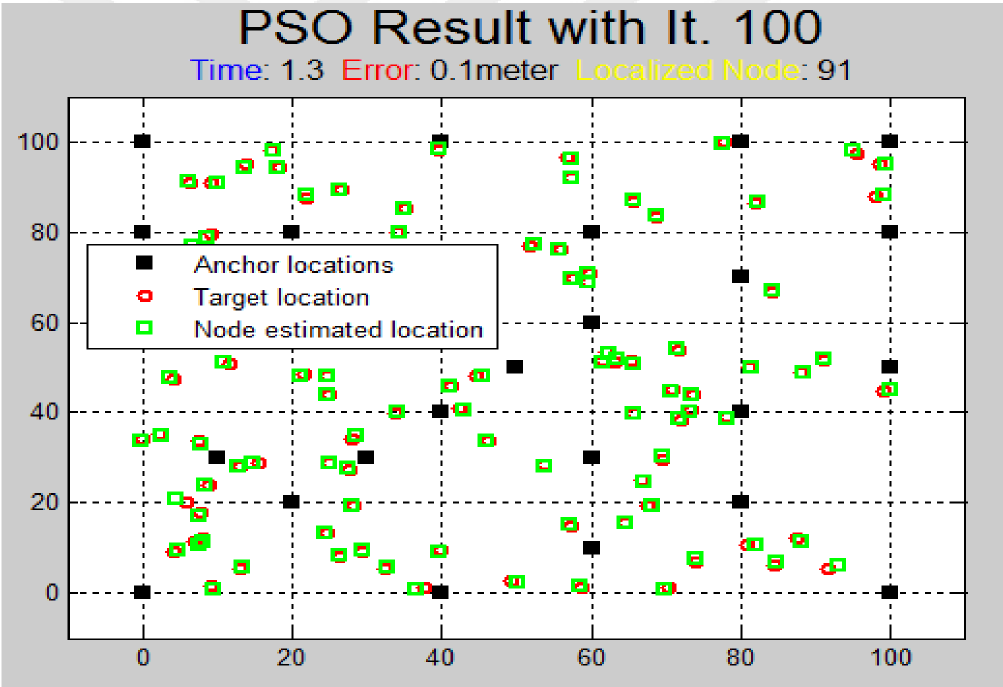

Figure 5.10: Experiment 4 of PSO Results with 25 Reporters and 100 Objectives Nodes

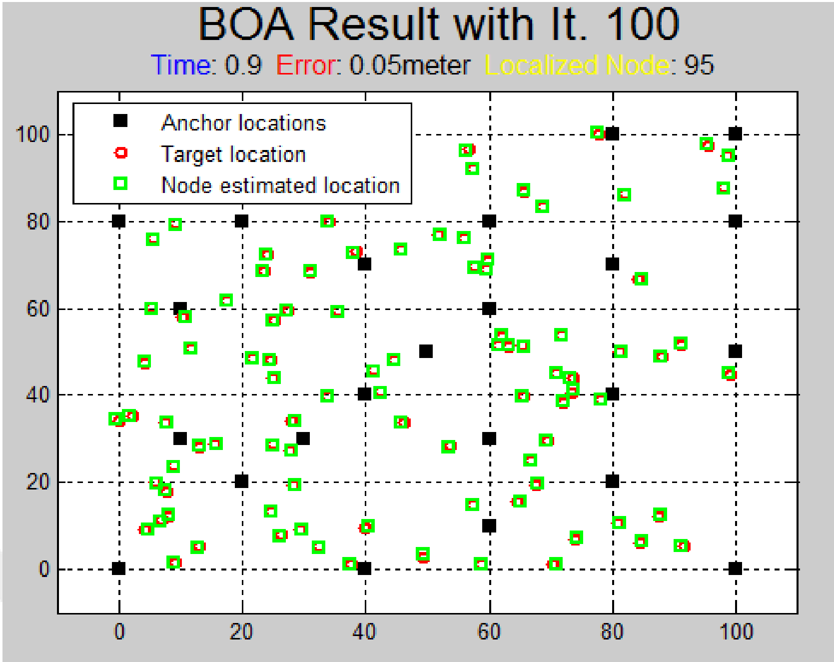

Figure 5.11: Experiment 4 of BOA Results with 25 Reporters and 100 Objectives Nodes

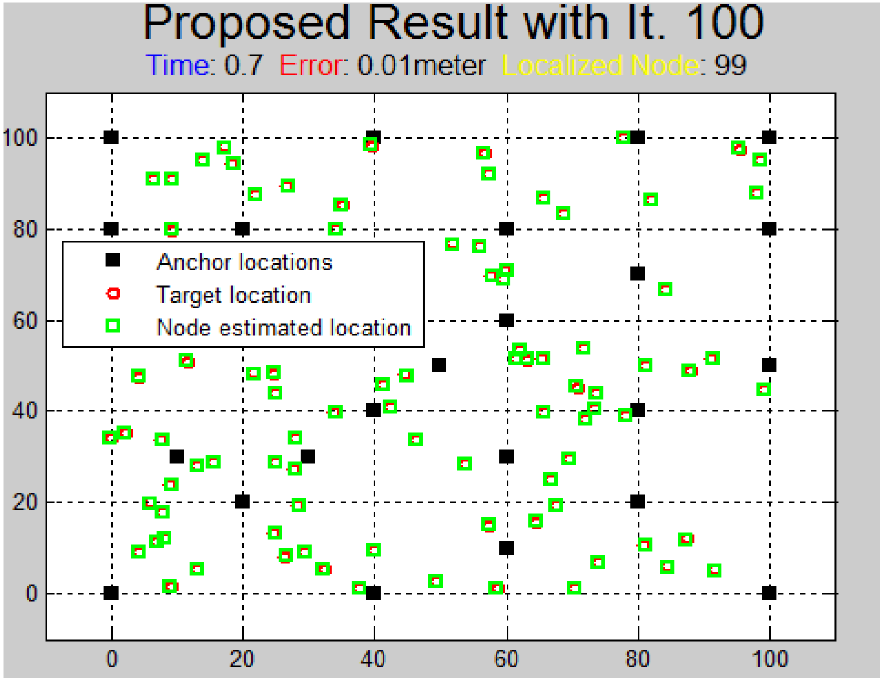

Figure 5.12: Experiment 4 of Proposed Method Results with 25 Reporters and 100 Objectives Nodes

In the previous experiment (final experiment) we used a simulation program for a 100-meter length and 100-meter-width display of 100 unknown nodes in a randomized manner and 25 of the anchor nodes are fixed and known position. We also compared three algorithms in several attempts. We noticed several observations, the proposed system achieved best results in time and a small error percentage compared to the rest of the systems. Where the proposed system achieved 0.01 error ratio at 0.7 seconds.

5.5 EVALUATIONS

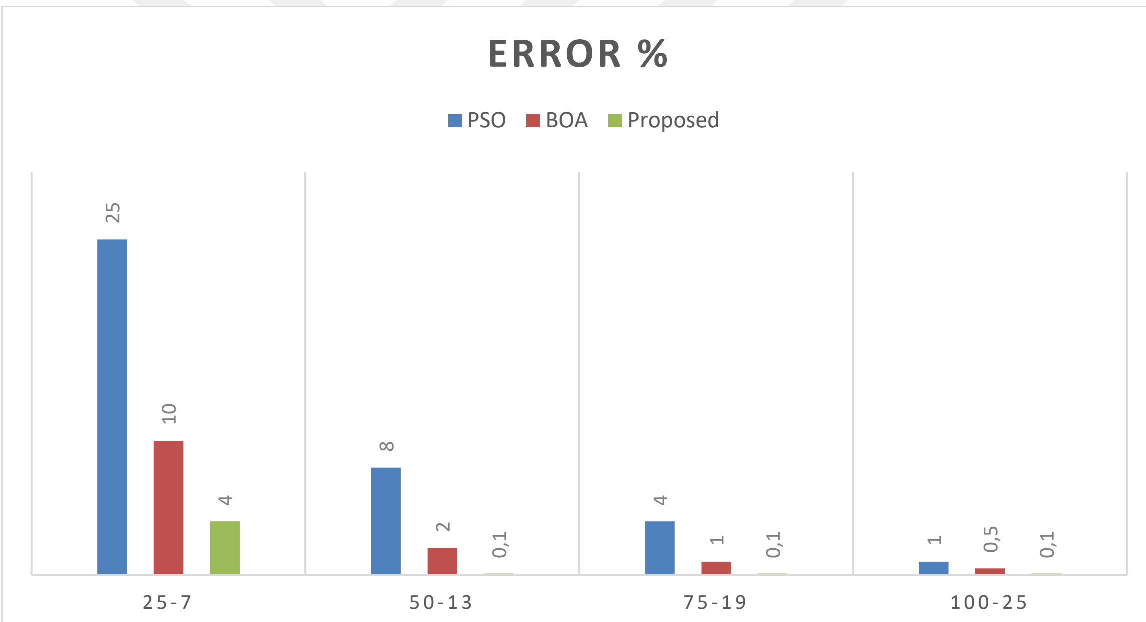

Figure 5.13: Error Percentages for each Localization Algorithm in Different Experiments

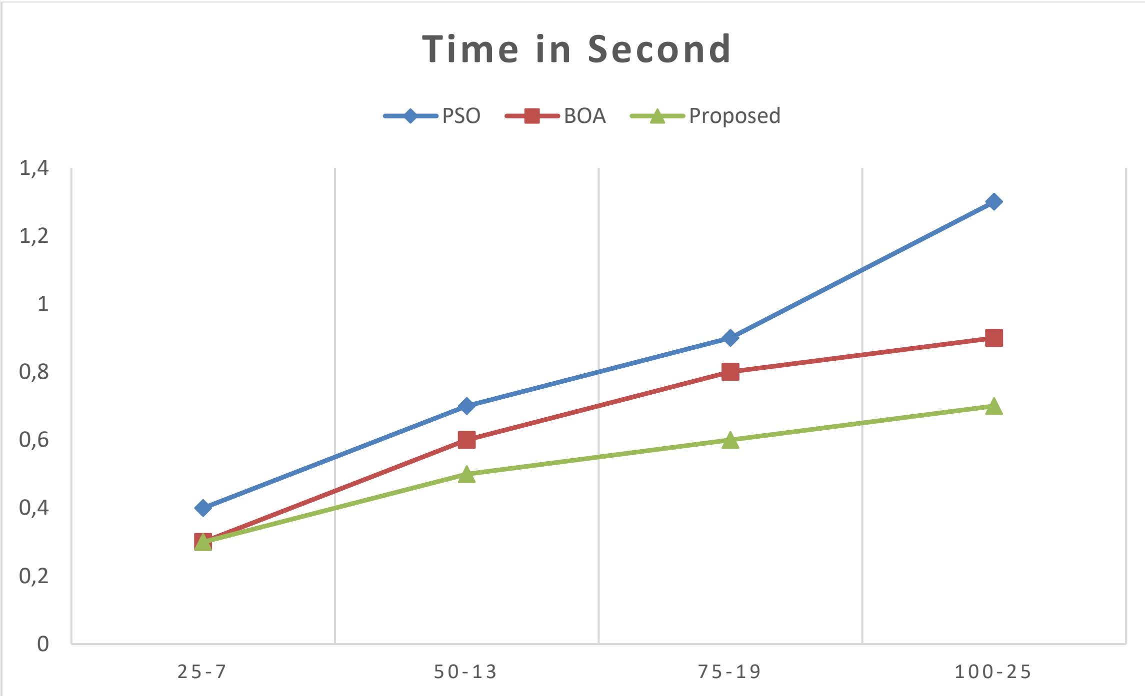

Figure 5.14: Time Diagram for each Localization Algorithm in Different Experiments

In figure 5.13 and 5.14, we found that proposed approach achieved the best performance and minimum error. We conducted four experiments with different settings and various number of reporter points and target points. The goal of each experiment to maximize number of localized points and minimize error. SSA achieved the target goal compared with other well-known approaches.

6. CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

Accurate node localization concerns many applications that adopt WSNs. In this paper, a node localization algorithm has been proposed based on a novel bio-inspired algorithm call Salp Swarm Algorithm (SSA) which handled the node localization problem as an optimization problem. The proposed algorithm has been implemented and validated in different WSN deployments using different numbers of target nodes and anchor nodes. Moreover, the proposed algorithm has been evaluated and compared to two well-known optimization algorithms, namely PSO and BOA, in terms of localization accuracy, computing time, and number of localized nodes. The obtained simulation results have proved the superiority of the proposed algorithm compared to the other localization algorithms regarding the different performance metrics.

6.2 FUTURE WORK

In this thesis we used an algorithm to locate some unknown nodes using some nodular coordinates but less information. We suggest that anyone who wants to complete this work in the future should use other algorithms that are faster (reduce the user time) or apply more than one algorithm at the same time, while increasing some experiments on the user in this thesis and increasing the number of nodes.

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