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Application des Méthaheuristiques pour l'Optimisation de la Localisation dans les Réseaux de Capteurs Sans Fil

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To my beloved parents
To my hasband
To my dearest sisters and brothers
To my sons Abdessamie and Abdelhadi.

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INTRODUCTION

Wireless Sensor Networks (WSNs) technology has been used in various applications such as habitat and environmental monitoring, surveillance, military applications, health care, disaster managements and others. Most of these applications need knowledge about locations of sensor nodes which send information collected from the monitored environment to know from where informations are received. In addition, for a large majority of applications, WSNs consist of an important number of randomly deployed sensor nodes. the random deployment is used due either to the hostility of the area to be monitored, or to its vastness. The location phase is therefore necessary not only for the operation of the network (geographical routing for example), but also for the exploitation of the collected data. Global Positioning System (GPS) [15] can be used for node localization, however GPS is not a feasible solution. It increases the cost and the energy consumption of the network. In addition, GPS is inaccessible in some area [45]. As alternative solution, researchers have been proposed to equip only a few nodes with GPS (anchor nodes). The rest of sensor nodes in the network (unknown nodes) estimate their locations based on position information given by anchor nodes via a localization algorithm.

Existing localization algorithms are diverse and suitable. But, unfortunately they suffer from the presence of error in the calculated positions which doesn't satisfy the need of some WSNs applications to have the most accurate positions of sensor node. So, these algorithms need to be enhanced by optimizing the error of localization.

Several techniques are proposed for localization optimization in WSNs such as machine learning techniques, meta-heuristic techniques, mobile anchor techniques and mathematical model for localization optimization techniques [95]. Among these algorithms, metaheuristic treat the localization in WSNs as an optimization problem [34]. These algorithms are widely used and they have shown their efficiency in solving the localization problem by obtaining good results [38, 20, 97].

The main goal of this thesis is to study the localization techniques and to develop an efficient new localization algorithms able to locate sensor nodes accurately. To acheive our aims, we propose two new localization algorithms using metaheuristic optimization algorithms. The first algorithm adopts the Social Spider Optimization metaheuristic (SSO) and the second uses the Cat Swarm Optimization metaheuristic (CSO) to enhance the localization precision of the traditional Centroid localization algorithm (CLA) by optimizing the error of localization.

Social spider optimization algorithm (SSO) is one of the new developed metaheuristic, this metaheuristic is invented in 2013. It is inspired from the cooperative behavior of the social spiders to resolve the optimization problems [87]. In this thesis, the SSO is used to reduce the localization error of the basic CLA. In the proposed algorithm, called CLA-SSO, which consists of an hybridization of two algorithms, CLA and SSO. the CLA is used firstly to find out the positions of unknown sensor nodes, second, the SSO is used to optimize these initial locations and reduce the localization error of the CLA method.

In the other hand, Cat Swarm optimization algorithm (CSO) is also one of the recent developed metaheuristic [88, 89]. This metaheuristic mimic the behavior of cats to resolve the optimization problems. In this thesis, we propose an enhanced localization algorithm called CLA-CSO based on this metaheuristic. The proposed algorithm is a combination between the CLA and CSO algorithms. The CSO is used to optimize the localization error of the basic CLA. The CLA-CSO runs in two steps, in the first step, the initial positions of unknown sensor nodes are estimated by using the CLA. These positions are optimized in the second step by the CSO metaheuristic and the optimal positions of unknown sensor nodes are found out.

In order to evaluate the performances of the proposed algorithms, Matlab platform is used as a tool for simulation. Results obtained by the proposed algorithms are compared with each other and with the traditional localization algorithm CLA in terms of localization accuracy. These results are obtained by changing some factors such as transmission radius, ratio of anchor nodes and the number of unknown nodes which affect the localization accuracy.

The thesis is divided into four chapters. First, we present the background of Wireless Sensor Networks including definitions topologies, applications and main challenges. After, the chapter 2 introduces the localization problem in WSNs. Chapter 3, highlights the localization optimization in WSNs where a new classification of localization optimization schemes is introduced, then a survey of some current related works on localization optimization using Meta-heuristic Optimization Algorithms are cited. The chapter 4 presents a detail explanation of our proposed approaches for localization optimization using SSO and CSO metaheuristics. Finally, conclusion and perspectives of the thesis are given in the conclusion section.

CHAPTER 1

BACKGROUND ON WIRELESS SENSOR NETWORKS

1.1 Introduction

Wireless sensor networks have become very popular and widely used in many applications. These networks use tiny devices called sensor nodes which communicate through the network and exchange informations.

The aim of this chapter is to introduce the concept of sensor node and to give an overview of Wireless Sensor Networks, their topologies, applications and some of their challenges.

1.2 The Sensor

Typically, WSNs are a resource constrained where sensor nodes are tiny devices which have limited battery power, processing speed, storage capacity and communication bandwidth. The main components of sensor node are a sensing unit, a processing unit, a transceiver and a power unit as shown in the figure1.1 [1, 77].

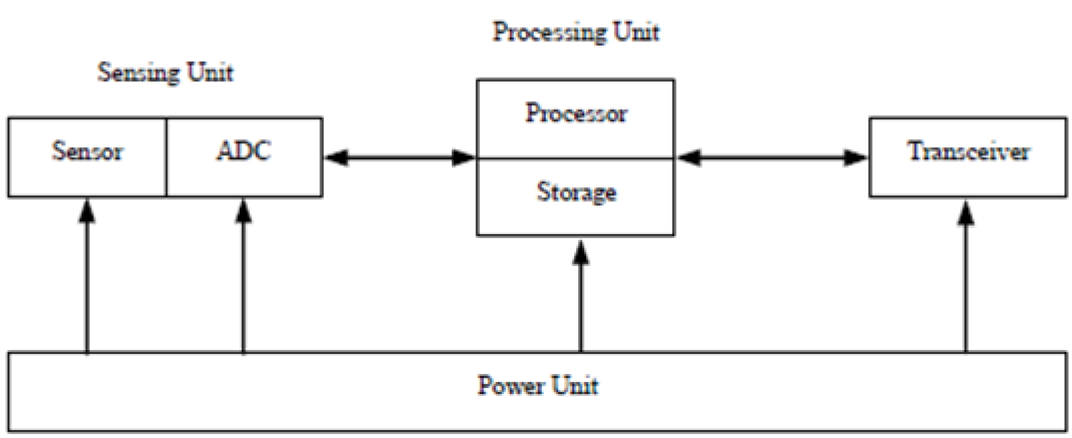

Figure 1.1: Sensor Node Components [1]

- **Sensing Unit:**

The function of the sensing unit is to measure the physical data from the area of interest and convert it from analog to digital signal by using the ADC converter. It will then be provided to the processing unit.

- **Processing Unit:**

  The processing unit is the main unit of the sensor node, it ensures collaboration with other sensor nodes to complete the desired task. This unit needs storage for local processing in order to minimize the size of messages sent.

- **Transceiver:**

  It is the communication unit, it allows the execution of all transmitted and received data. Different communication schemes can be deployed in this unit such as optical communication (laser), infrared, and radio-frequency (RF).

- **Power Unit:**

  the main function of this unit is the control of the sensor node energy consumption and lifetime. Sensor node is fitted with rechargeable or non-rechargeable batteries.

1.3 Wireless Sensor Networks

1.3.1 Definition

Wireless Sensor Networks (WSNs) consist of an important number of costly effective sensor nodes which are deployed for collecting informations about the environment which to be monitored such as temperature, sound, vibration, pressure, motion or polluants [2].Sensor nodes communicate through wireless communication and cooperate to send their data to the base station or sink which plays a role of interface between the network and users. The general architecture of a Wireless sensor networks is shown in the following figure [3].

Classification of WSNs, their topologies, many of their applications and challenges are discussed in the next section.

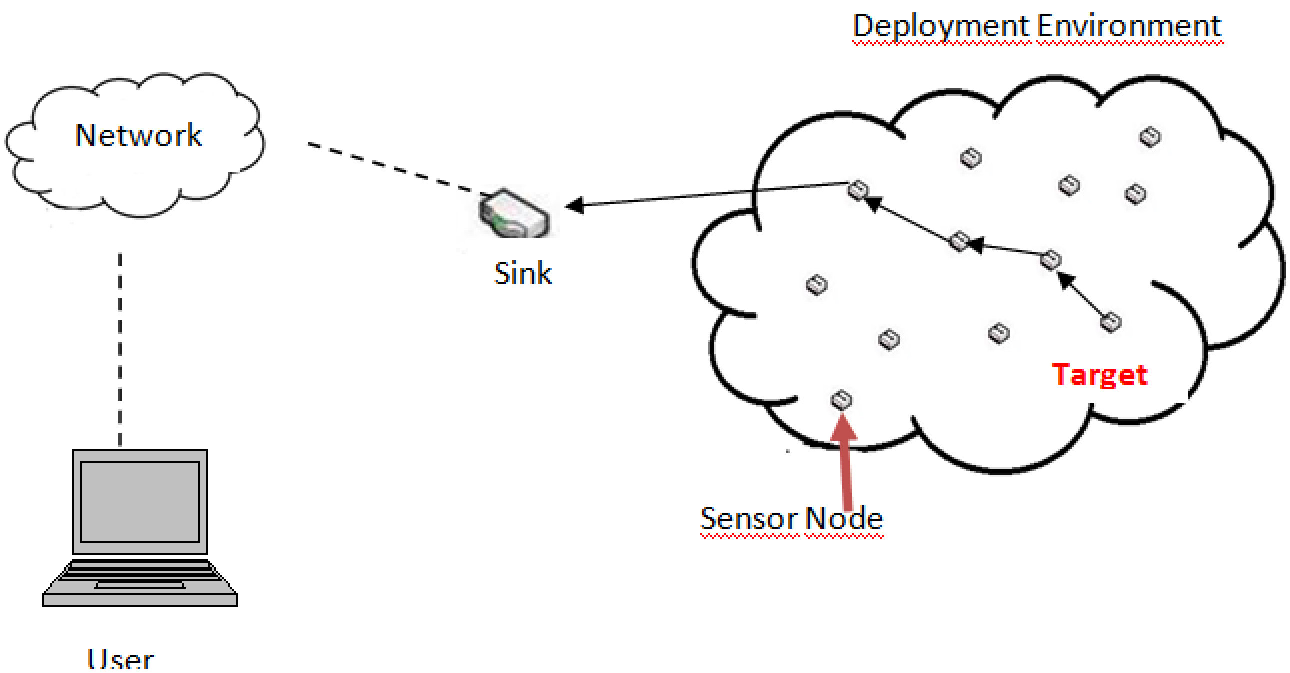

Figure 1.2: WSNs architecture

1.3.2 Node Deployment

Deployment is the process of setting up nodes in the area of interest (environment which to be monitored), it can be either deterministic or random.

- **Deterministic Deployment:** In this type of deployment, sensor nodes are placed in known positions.
- **Random Deployment:** In this type of deployment, sensor nodes are randomly deployed, thus they need a localization system to localize them self

1.3.3 Classification of WSNs

WSNs can be classified into different types depending on the nature of the deployment environment including terrestrial, underground, underwater, multimedia and mobile WSNs [3, 5, 81].

In terrestrial WSNs, the sensor nodes can be placed in either indoor environments such as inside building or in outdoor environments such as forest or battle fields. In this type of WSNs, sensor nodes must be capable of communicating their data to the sink. In addition sensor nodes are generally equipped with secondary battery for power because the primary battery power is limited and may not be rechargeable.

Underground WSNs are deployed in caves or mines for monitoring underground conditions. Additional sinks are generally placed underground to facilitate the delivery of data from the sensing sensor nodes to base station. For these WSNS, communication is a main challenge due to the difficulties of communication via soil, water, rocks, and alternative mineral contents.

Underwater WSNs consists of sensor nodes placed underwater such as seas or oceans. In these WSNS, the cost of sensing sensor nodes is high and need autonomous underwater vehicles to gather their data. Communication within underwater environment can be done via acoustic waves which present many problems such as limited bandwidth, long propagation delay, high latency and signal fading problems.

Multimedia WSNs are intended to monitor events of many multimedia systems such as video, audio and imaging. These WSNs include sensor nodes equipped with microphones and cameras. Multimedia WSNs face many challenges such as high energy consumption, quality of the service provisioning, compression techniques and processing.

Mobile WSNs include sensor nodes which can moving (mobile nodes). Mobile nodes have the same capabilities as static nodes including sensing and communication. Main challenges of mobile WSNs are deployment, localization, navigation, self-organisation and coverage, management, maintenance and energy consumption.

1.3.4 Topologies of WSNs

There are three main topologies of WSNs, centralized topology, distributed topology and decentralized topology [2, 5].

1.3.4.1 A Centralized Topology

In the centralized topology, the communication is between the base station and the sensor nodes in the network. Although, this topology is simple, it requires that the base station to be within transmission radius of all the sensor nodes.

1.3.4.2 A Distributed Topology

In the distributed topology, each sensor node in the network can communicate with its neighboring sensor nodes (nodes within its transmission range). In this topology, if a sensor node desires to send a message to another sensor node outside its transmission range, it uses the multi-hop communications which allows the use of intermediates sensor nodes to forward the message to the desired sensor node.

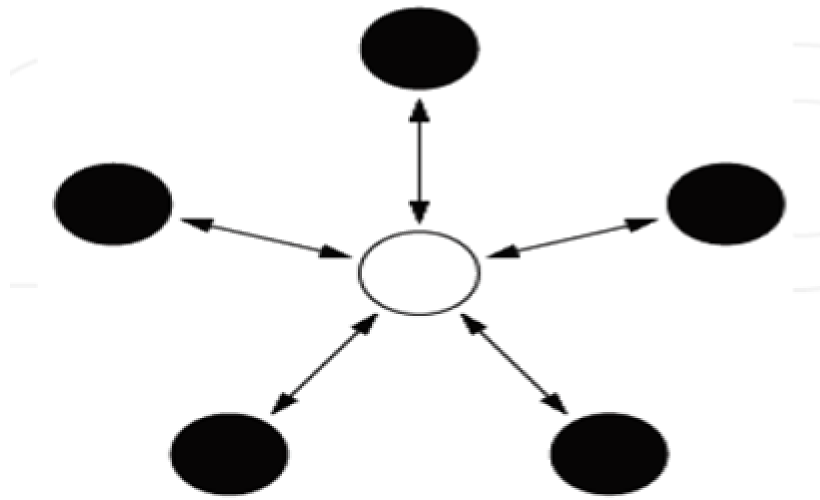

Figure 1.3: A centralized topology of WSNs

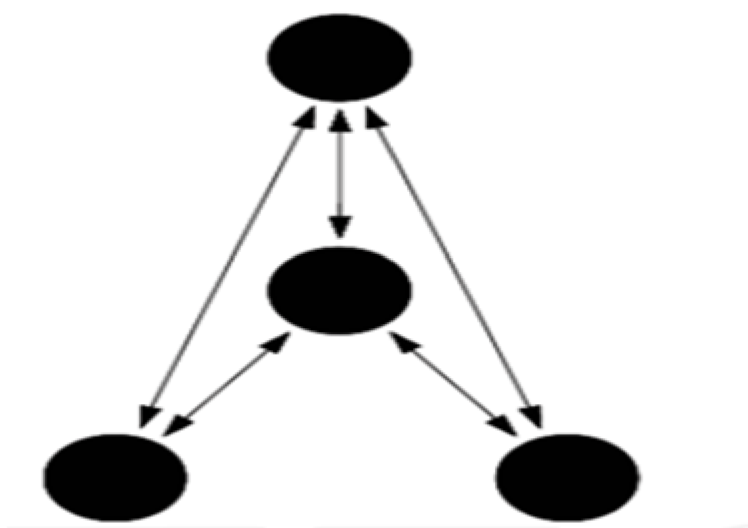

Figure 1.4: A distributed topology of WSNs

1.3.4.3 A Decentralized Topology

The decentralized topology is an hybridization between the two previous topologies. In this topology, sensor nodes are distributed into clusters and only some of them are capable to forward message through multi-hop communications.

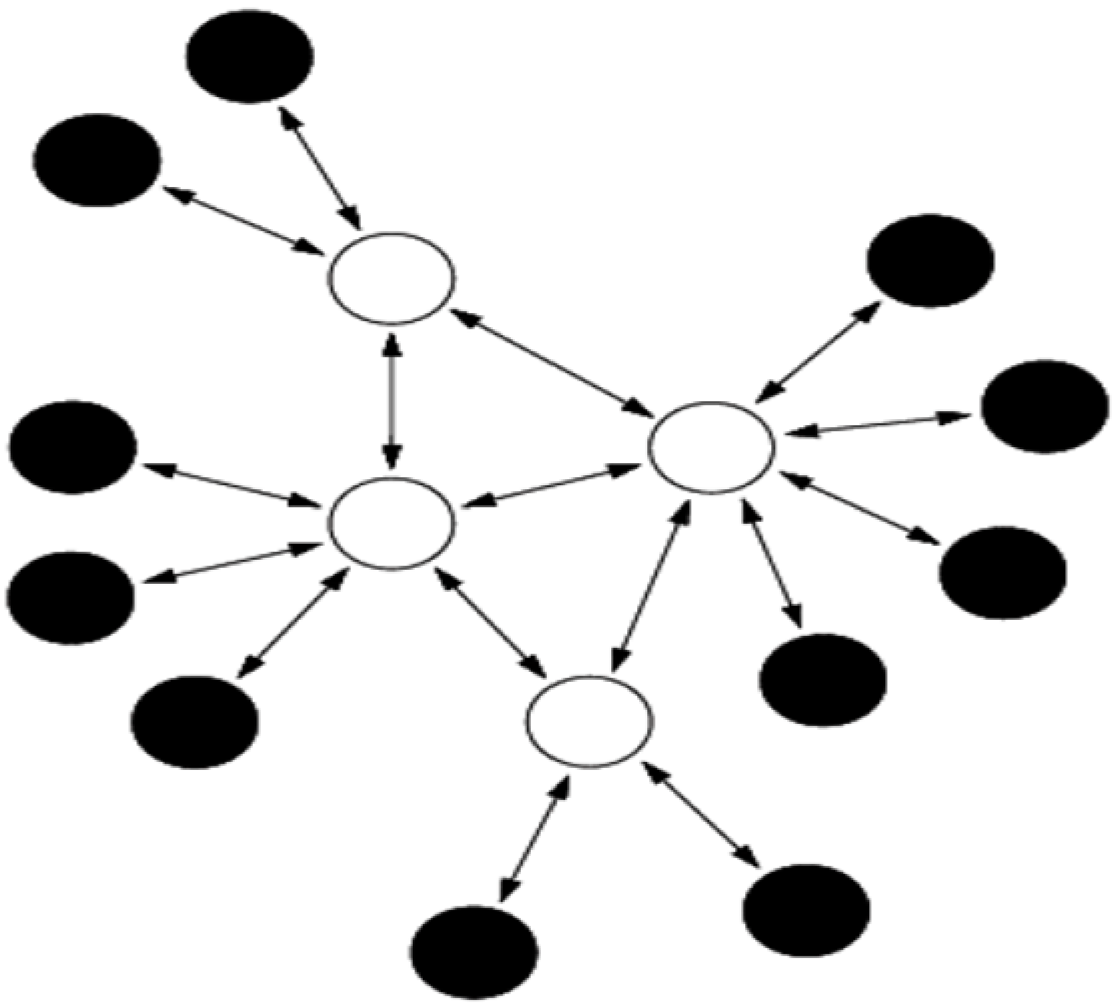

Figure 1.5: A decentralized topology of WSNs

1.3.5 Applications of WSNs

WSNs are used in wide range of applications such as environmental applications, health applications, security applications and others [6, 9, 10, 79]. In general, these applications can be either monitoring or tracking applications [7].

Environmental applications include some applications intended for animal tracking, forest surveillance, flood detection, weather forecasting [8], air pollution monitoring, greenhouse monitoring, landslide detection [2] and many others.

The use of wireless sensor networks in environmental applications can improve knowledge of the environment and the efficiency of control means. Thus WSNs can contribute to the development of systems for risk response, natural disaster detection, and other systems.

Health applications of WSNs include medical treatment, pre and post-hospital patient monitoring, life saving applications [6], etc. In addition, WSNs can give interfaces for the disabled, integrated patient monitoring, diagnostics, and drug administration in hospitals, tele-monitoring of human physiological data, and tracking and monitoring doctors or patients inside hospitals [2].

WSNs can be also used by some institutions to monitor their infrastructures in order to prevent possible theft or fire. They can also be used to secure critical buildings and facilities like as power plants, airports, and military bases [8].Thus, security applications of WSNs play an important role.

In addition to the above mentioned applications of WSNs, we can list other applications such as industrial sensing applications [2, 6] transportation applications [2] and many others.

1.3.6 Challenges of WSNs

WSNs face many challenges [3, 80], some of them are listed in the following subsection:

1.3.6.1 Resource Constraints

The implementation of WSNs requires to taking into consideration resources constrained:

- Limited energy.
- Limited memory.
- Limited computational capability.

1.3.6.2 Dynamic Topologies and Hard Environmental Conditions

The topology of WSNs can change due to failure of sensor nodes. Nodes can fail due to hardware problems or physical damage or by exhausting their energy supply[2]. In addition, sensor nodes can be deployed in hostile zone that are sometimes hard and difficult to access, such as active and dangerous volcanoes to monitor their activity, battlefields beyond enemy lines, inside a large machine, at the bottom of an ocean, inside a tornado, in biologically or chemically contaminated fields [6].

For this, sensor nodes must be designed in such a way as to be able to resist to different and severe conditions of the environment [4], such as high heat, heavy rain, humidity, loud noises, etc.

1.3.6.3 Quality-of-Service Requirements

Quality of service requirements vary from application to another of WSNs. it refers to the accuracy between the information received by the base station and the real information the event sensed by sensor nodes.

1.3.6.4 Scalability

Depending on the application, the number of deployed sensor nodes in WSNs can vary from hundred to thousand nodes or even more. Theses sensor nodes are also deployed in different densities. Thus the deployed protocols of WSNs must be scalable in both cases: when the number of sensor nodes increases and when the density of deployment increases.

1.3.6.5 Production Cost

Due to the important number of deployed sensor nodes in the network, the cost of whole network can be expensive. If that cost is more expensive than the use of traditional sensor nodes, then the sensor network is not cost effective.

1.3.6.6 Security

Wireless networks are vulnerable to different types of attacks. We can distinguish either active or passive attacks. Passive attacks are carried out by spying wireless transmissions. Active attacks consist of modification, fabrication and interruption such as node capturing or routing attacks. Thus, security is a very important factor that needs to be taken into account in the design of WSNs.

1.4 Conclusion

In this chapter, an overview of wireless sensor networks is given. We have shown that in many applications of WSNs, the deployment of sensor nodes is done in a random way where sensor nodes constituting the network are placed in unknown places. In such a case, to know their positions and ensure the best functioning of the network, sensor nodes need a localization system, which make of localization one of main challenges of WSNs. This task is discussed in the next chapter.

CHAPTER 2

LOCALIZATION IN WSNS

2.1 Introduction

Localization is considered as one of the main challenges in WSNs. This chapter, explains the localization problem in WSNs then gives a brief overview of different algorithms used to resolve this problem and highlights the criteria which can be used to evaluate their performances.

2.2 Localization in WSNS

WSNs can be composed of two types of sensor nodes, the unknown sensor nodes and the anchor sensor nodes. The unknown sensor nodes are nodes with unknown locations and need to be localized. The anchor sensor nodes represent a few number of sensor nodes with known locations. Localization in WSNs is the process of determining positions of the unknown sensor nodes forming the network [13, 19, 82, 11, 10].

2.2.1 Location Determination Techniques

After determining its distance from a number of anchors, an unknown node can locate itself. For this, there are three main techniques that are used for most localization algorithms [10, 11].

2.2.1.1 Trilateration Technique

In this technique, the node determine its position from the intersection of 3 circles that are formed based on distance measurements from its 3 neighbouring anchor nodes as shown in the following figure.

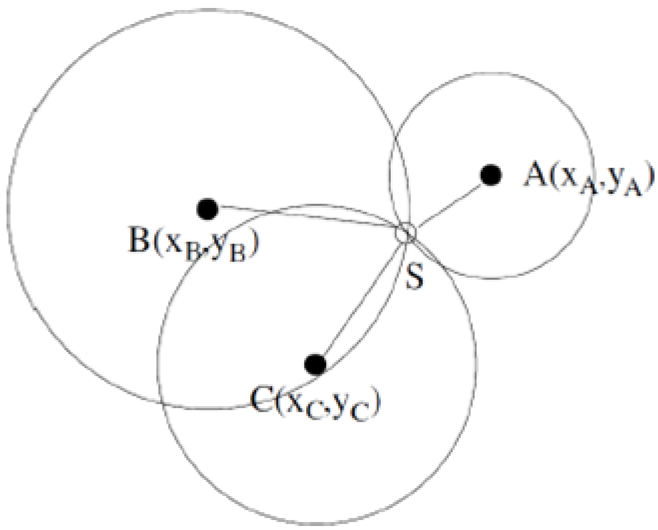

Figure 2.1: Trilateration technique [11]

2.2.1.2 Multilateration Technique

In real world, the distances cannot be exactly calculated, As a result, trilatiration technique presents a high error in the positions calculation. To minimize this error, including the distance measurements from multiple neighbouring anchor nodes is a possible solution as shown in the following figure.

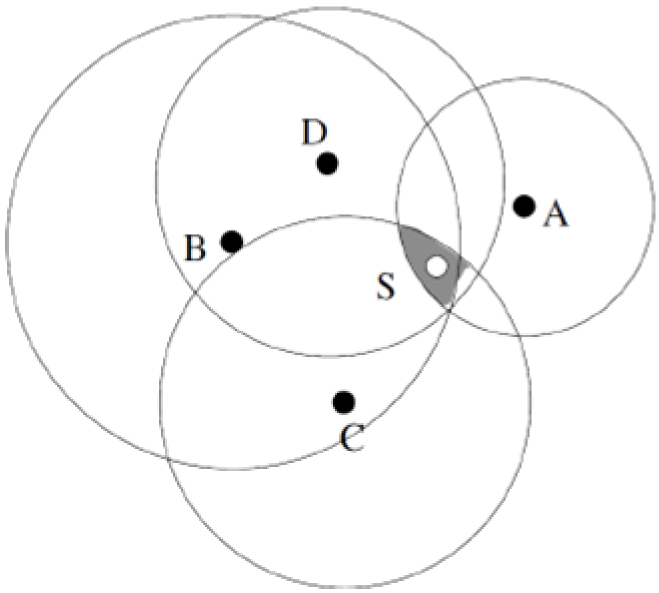

Figure 2.2: Multilateration technique [11]

2.2.1.3 Triangulation Technique

This technique uses the trigonometry laws of sines and cosines to calculate the nodes locations. It based on the estimated angles from three anchor nodes and their positions as shown in the following figure.
This technique is similar to trilateration. Indeed, distances between the unknown sensor node and its neighbouring anchor nodes is deduced based on the angles of arrival.

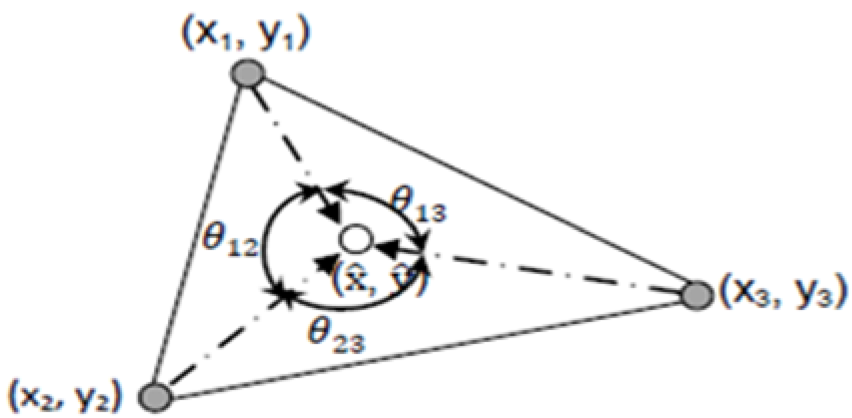

Figure 2.3: Triangulation technique [11]

2.2.2 Classification of Localization Algorithms

There have been many algorithms proposed to locate the unknown sensor nodes. These traditional algorithms are classified in different way according to some key features including the use or not of anchor nodes, the network configuration and mobility, the distribution of the calculation process and hardware capabilities [11, 14, 82] as shown in the figure 2.4.

2.2.3 Use of Anchor Nodes

Anchor sensor node is a sensor with known position either via GPS or by manual deployment. Based on the use of anchor nodes or not, we can distinguish two types of localization algorithms: the anchor based and the anchor free algorithms.

- **Anchor Based Localization Algorithms:** These algorithms estimate the unknown sensor node position by the help of the locations information of neighboring anchor sensor nodes.

- **Anchor Free Localization Algorithms:** These algorithms don't need the locations information of anchor nodes to estimate the unknown sensor nodes positions.

2.2.4 Considering the Network Mobility and Configuration

Considering the sensors mobility, we can distinguish four types of network configuration:

- **Static Nodes**
- **Mobile Sensors and Static Anchors**
- **Static Sensors and Mobile Anchors**
- **Mobile Sensors and Mobile Anchors**

When the sensor nodes are static or not moving, the algorithm is called static localization algorithm. When the nodes have some mobility, the algorithm applied for localization is called dynamic localization algorithm [24].

2.2.5 Considering the Distribution of Calculation Process

When we consider the distribution of the calculation process, localization algorithms can be classified into two categories based on where the sensor nodes positions are calculated [14]: centralized and distributed algorithms.

- **Centralized Algorithms:** In the centralized algorithms, the sensor nodes positions are calculated by a central location using the sent inter-sensor measured distances.

- **Distributed Algorithms:** In these algorithms, each sensor node calculates its position by using the distance measured from other anchor nodes.

2.2.6 Considering Hardware Capabilities

With regard of hardware capabilities, the localization schemes can be classified into two categories: Range based and range free schemes [19].

- **Range Based Schemes:** these algorithms use extra hardware capabilities to inter-sensors distances determination, the popular Range based techniques use Received Signal Strength Indicator (RSSI), Time of Arrival (ToA), Time Difference of Arrival (TDoA) and Angle of Arrival (AoA) to inter-sensors distances estimation [13, 19]. These algorithms are more accurate but the requirement of additional hardware makes it expensive. Hence, these methods are generally not preferred.

- **Range Free Schemes:** The range free algorithms based on the connectivity between sensor nodes, it use the content of messages circulated in the network between sensor nodes (anchor and non anchor sensor nodes) [19] to estimate the unknown sensor nodes positions. Compared with range-based algorithms, range free schemes achieve low accuracy but provide cost effective localization. The most used range free algorithms [13] are Distance Vector-Hop (DV-Hop) and Centroid localization algorithms.

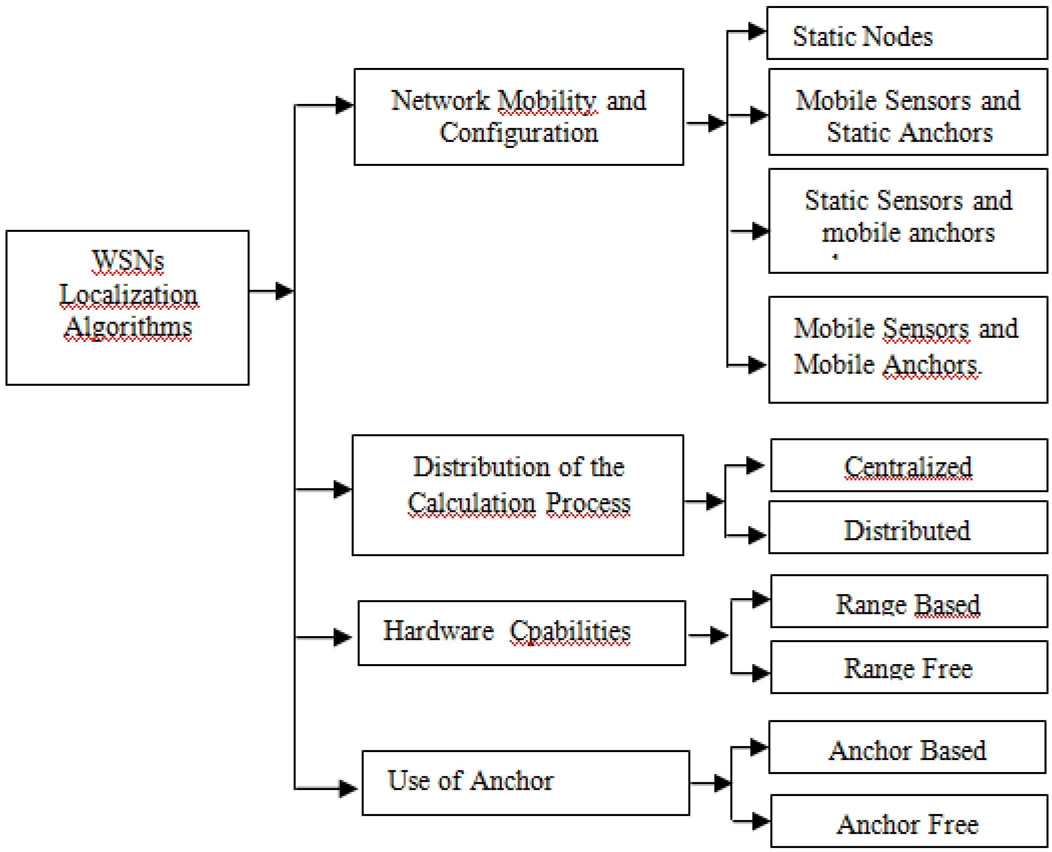

Figure 2.4: Classification of localization algorithms

2.2.7 Challenges For Localization In WSNS

Localization algorithms have many challenges that need to be cope to enhance the localization process, including accuracy in computing positions, localization in mobile WSNs, transmission range, energy consumption, scalability, localization security and localization in three dimensional spaces[13, 35].

2.2.7.1 Accuracy in Computing Positions

Localization accuracy refers to the difference of distance between the real position and the estimated one of the sensor node. Localization algorithms seek to get the most possible accurate positions of sensor nodes. Thus, optimization algorithms are needed to be used to improve the localization accuracy.

2.2.7.2 Localization in Mobile WSNs

WSNs can either static or dynamic.In dynamic WSNs sensor nodes can be moving. Thus, to get periodically positions of sensor nodes in such network is an important challenge for localization algorithms.

2.2.7.3 Transmission Range

The performance of some localization algorithms is not the same for different transmission radius, therefore, to set the appropriate transmission range to get the most accurate localization is a challenge to be addressed for localization algorithms.

2.2.7.4 Computational Complexity

Computational complexity in WSNs localization is the complexity of the localization algorithm, which means the position calculation speed. It is a challenge to decrease the computational complexity of the localization algorithms to increase the lifetime of the whole network because the computation spends the energy.

2.2.7.5 Scalability

Scalable localization of a localization scheme means that its performance is the same when its scope become of considerable size. Localization systems need to be scalable in three cases: first, when the deployment area size increases, second when the density of the nodes increases and finally when the dimension of deployment area changes (from 2-dimension to 3-dimension network).

2.2.7.6 Localization Security

Localization process may face many attacks if WSNs is deployed in insecure area. Thus, security is an important challenge for localization algorithms.

2.3 Background of Some Localization Algorithms

In this section, some localization algorithms will be reviewed including, Centroid Localization Algorithm (CLA), MDS-MAP, Distance Vector Hop (DV-Hop) and Aproximate point in triangulation (APIT)[11, 4, 96].

2.3.0.1 CLA

Centroid localization algorithm (CLA) is proposed by Bulusu et al. [83, 84]. In this algorithm, when the unknown sensor node receives position information from at least three anchor sensor nodes within its transmission range, it localizes itself based on those informations.
The location of an unknown sensor node is calculated by the following equation:

$$(X_{est}, Y_{est}) = (\frac{\sum_{a=1}^{k} x_a}{k}, \frac{\sum_{i=1}^{k} y_a}{k}) \tag{2.1}$$

Where: (X_{est}, Y_{est}) is the estimated position of the unknown node and k is the number of anchor sensor nodes within the transmission range of this unknown sensor node.
An example of localization by CLA using three anchor nodes is given in the following figure.

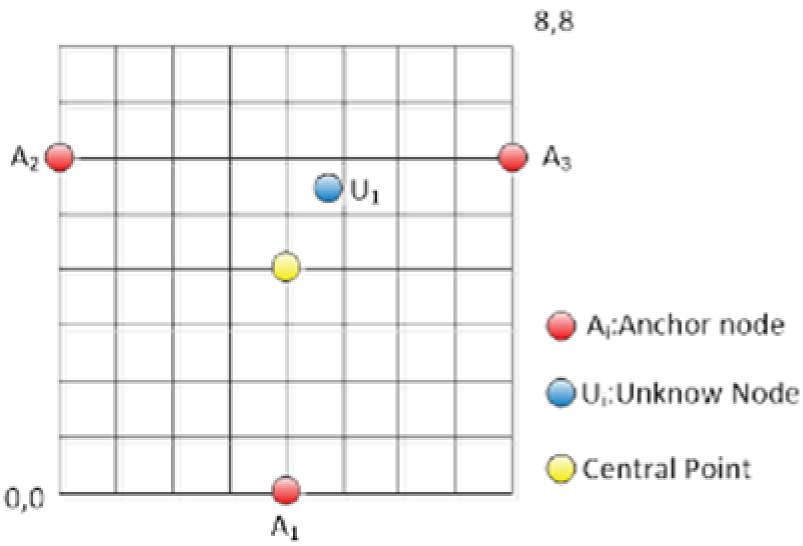

Figure 2.5: Centroid Algorithm Example [70]

The CLA has the advantage that it is simple and uses few parameters; however, it calculates the unknown sensor nodes coordinates with large error [13, 14, 86]. In order to enhance the localization accuracy of the CLA, several modified version of this algorithm have been proposed such as in [85]. In this work the unknown sensor nodes coordinates are calculated based on weights which are proportional to the distance between Anchor and unknown sensor node. The position calculation is given according to the following Equation:

$$(X_{est}, Y_{est}) = \left(\frac{\sum_{a=1}^{k} x_a * w_a}{\sum_{a=1}^{k} w_a}, \frac{\sum_{a=1}^{k} y_a * w_a}{\sum_{a=1}^{k} w_a}\right) \tag{2.2}$$

Althoug the proposed improved version reduced the localization error but the error is steel high.

2.3.0.2 APIT

This algorithm is a range free algorithm [83, 70]. In this algorithm, triangular areas are created by anchor nodes towards the unknown sensor node. The intersection of triangular areas is a polygonal area. The centroid point of this polygonal area is the coordinates of the unknown sensor node. the localization accuracy of APIT depends on the number of anchor nodes in the neighboring of the unknown sensor node. In order to improve the accuracy of APIT, a limited number of nearest anchor nodes is used for estimating unknown nodes positions. The triangular areas and the centroid point determined by four anchor nodes in APIT are shown in the following figure:

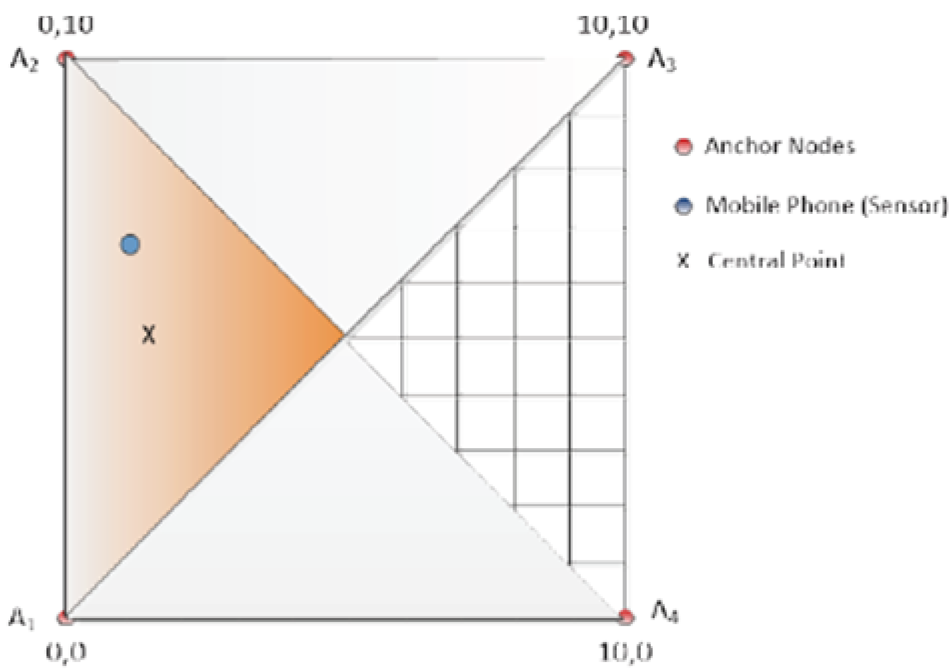

Figure 2.6: APIT Localization Algorithm Example [70]

2.3.0.3 MDS-MAP

This algorithm estimates the unknown sensor nodes positions without using information about anchor sensor nodes locations [11]. It uses a multidimensional scaling (MDS)technique. MDS utilizes information of inter-nodes distances to create a map of the search space. MDS-MAP is a range free localization algorithm where inter-sensor distances are estimated by using hops.

2.3.0.4 DV-Hop

This algorithm is a range free localization algorithm [83]. It estimates the unknown sensor nodes positions based on the connectivity information between anchor nodes and unknown sensor nodes. the localization process by this algorithm is achieved by following many steps. In the first step, all anchor nodes broadcast the information of their positions. These informations are propagated hop by hop and a hop counter is memorized in a table to calculate a minimum hop of the unknown node from each anchor node. In the second step, the average hop distance is calculated by an anchor sensor node when it receives a message from another anchor sensor node.Finally, each unknown sensor node position is estimated by using the multilateration method.

The DV-Hop has the advantage that is a free range algorithm, but calculates unknown sensor nodes positions with high error.

2.4 Evaluation Metrics for Localization in WSNs

Several evaluation criteria can be used to evaluate the performance of localization [82] including: average localization error, root mean square error, geometric mean error.

- **Average Localization Error:** it can be calculated as follows:

$$error = \frac{1}{N_t}\sum_{i=1}^{N_t}\sqrt{(x-x_e)^2+(y-y_e)^2} \tag{2.3}$$

Where:N_t is the number of localized nodes, (x, y) the real positions of the unknown sensor node and (x_e, y_e) its estimated positions.

- **Root Mean Square Error:** it can be computed as follows:

$$error = \sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}((x-x_e)^2+(y-y_e)^2)} \tag{2.4}$$

- **Geometric Mean Error:** it can be calculated as follow:

$$error = \sqrt{\prod_{i=1}^{N_t}((x-x_e)^2+(y-y_e)^2)} \tag{2.5}$$

2.5 Conclusion

The localization problem remains an open issue despite the number of research works that have been attached to it In this chapter, we have seen that sensor nodes in WSNs localize themselves by the help of known location information of at least three anchor sensor nodes. We have seen also that the main weakness of the traditional localization algorithms is the presence of error in positions calculation which does not meet the needs of some applications to know the most possible accurate positions of sensor nodes. As a result, these schemes need to be optimized. All this leads to thinking about using optimization techniques for localization in WSNs.

CHAPTER 3

LOCALIZATION OPTIMIZATION IN WSNS USING META-HEURISTICS OPTIMIZATION ALGORITHMS

3.1 Introduction

In the real world, many problems as localization in WSNs are considered as optimization problems. For these problems, there is no analytical method that can solve them efficiently in a reasonable time. In fact, the complexity of analytical methods increases with the increase of the problem size. This has led researchers to opt for optimization methods as an alternative to analytical methods.

Metaheuristics are among optimization algorithms which have shown their effectiveness and robustness in solving several optimization problems. Localization in WSNs can be considered as one of the optimization problem due to the size and the complexity factors.

3.2 Localization Optimization in WSNs

The traditional localization algorithms suffer from the presence of error in the calculated positions, this error is caused by the error in the calculation of distances between the anchor nodes and the other nodes forming the network. For this, several techniques have been done to enhance the localization performances and give the optimal positions of all the unknown nodes in the network.

There are a few amounts of papers that review the techniques adopted for localization optimization. For example, S. Sivakumar et al. [19] presents a survey and classification of localization techniques. The authors classified localization techniques as range-based localization techniques, range-free localization techniques, hybrid localization techniques, mobile anchor based localization techniques and evolutionary based localization techniques. Some other works that deal with each class of localization optimization techniques separately, such as the survey presented by G. Han et al. In [12] which review the most effective mobile anchor node assisted localization techniques. This paper given also a classification of mobile anchor node assisted localization algorithms based on the movement trajectories followed by the mobile anchors. In [50] S. Pandey gives a survey of different machine learning techniques that are used to overcome the node localization problem. In this paper a comparative table between the different algorithms is presented. In [48], S.S. Mohar et al. presented a survey of meta-heuristics used to address the localization issue. This paper presented a comparison between existing optimization techniques used for node localization.

3.2.1 Classification of Localization Optimization Methods

The lack of proposed classification of algorithms adopted for WSNs localization optimization has motivated us to propose a new taxonomy in this thesis. These algorithms are classified as machine learning based localization optimization techniques, meta-heuristics based localization optimization techniques, mobile anchor node based localization optimization techniques and mathematical models for localization optimization.

Our proposed taxonomy of localization optimization techniques is given in the following figure and the review of these techniques is given in the following subsections:

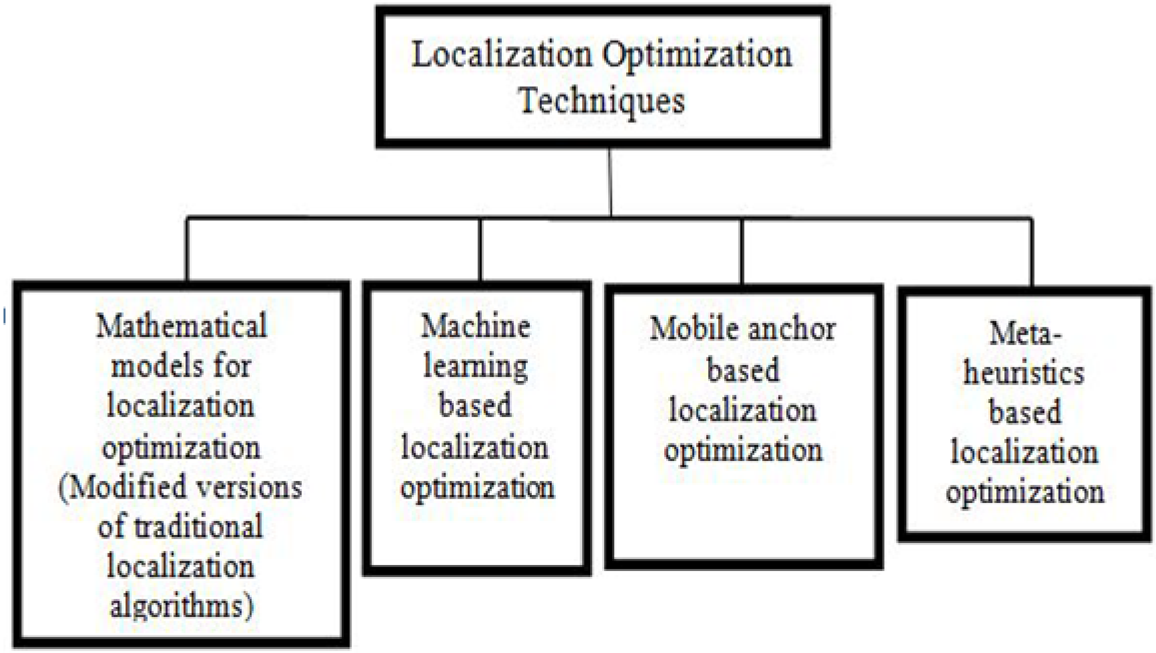

Figure 3.1: Classification of localization optimization algorithms [95]

3.2.1.1 Mobile Anchor Based Localization Optimization

Mobile Anchor Node Based Localization Optimization Technique (MANL) is a promising method to WSNs localization [12]. In this method, one or more mobiles anchors equipped with GPS unit traverse the network and periodically broadcast a packets contains their current locations to assist neighboring unknown nodes locate themselves [13]. Hence, MANL techniques can beneficially reduce the cost of using GPS and the energy consumption. it can improve the localization accuracy by designing a good movement trajectory of the mobile anchor nodes. MANL algorithms are classified into two categories: localization based on mobility model and localization based on path planning scheme. The comparison between localization based on mobility model and localization based on path planning scheme in [12] shows that localization algorithms based on path planning scheme are more efficient than localization algorithms based on mobility model in terms of computation complexity, energy consumption, ratio of localized nodes and localization accuracy.

3.2.1.2 Machine Learning Based Localization Optimization

Machine learning algorithms use experiences to create predictive model, it can be classified into two categories [50]: supervised learning algorithms and unsupervised learning algorithms. Supervised learning algorithms used in WSNs localization optimization include Decision Tree (DT) [74], Neural Networks (NNs) [72], Support Vector Machines (SVMs) [83] and others. Optimization Reinforcement Learning [50] and Self-Organizing Map [75] are some of unsupervised learning algorithms used in WSNs localization.

3.2.1.3 Mathematical Models Based Localization Optimization

To perform better localization results obtained by traditional localization algorithms, several researches have been done based on improvements in these algorithms. Based on the determination of possible reasons for errors the algorithm is improved. For traditional DV-HOP algorithm, the two main factors that affect its localization accuracy are minimum hops and average hop distance [15]. According to this analysis, different authors proposed new localization algorithms that consist of improved versions of traditional DV-HOP algorithm. Main improvements based on average hop distance, minimum hops and based on node deployment information and nearest anchors [13, 17]. Limitations of centroid localization algorithm have been also detailed in several researches, with the aim to propose a modified form of this algorithm [51].

3.2.2 Meta-heuristics Based Localization Optimization

Metaheuristic algorithms are widely used in recent years to solve the localization problem, which may be due to their simplicity, fast convergence, and the optimality of the results. With meta-heuristics, the localization problem is formulated as single or multi objective function which are to be optimized using one or either hybrid meta-heuristic algorithm [31, 56, 76]. Meta-heuristics or bio-mimetic algorithms became popular and active research in WSNs localization as they are robust and effective [36]. The main objective of these algorithms is to minimize positions estimation error and increase the localization accuracy.

3.3 Meta-heuristic Algorithms

Metaheuristic algorithms are general optimization algorithms [20], they are used to solve a broad range of optimization problems. These algorithms are nature inspired, approximate, which means that they give an approximate solution and not the exact. They use an iterative process where they start by a set of initial solutions. The previous solutions are replaced by other neighboring solutions which are considered better in terms of an objective function in the next iteration .

Metaheuristic algorithms can be classified into four categories [38]: Evolutionary algorithms, Swarm-based algorithms, Human-based algorithms and Physics-based algorithms. Each group includes many metaheuristics as shown in the following figure.

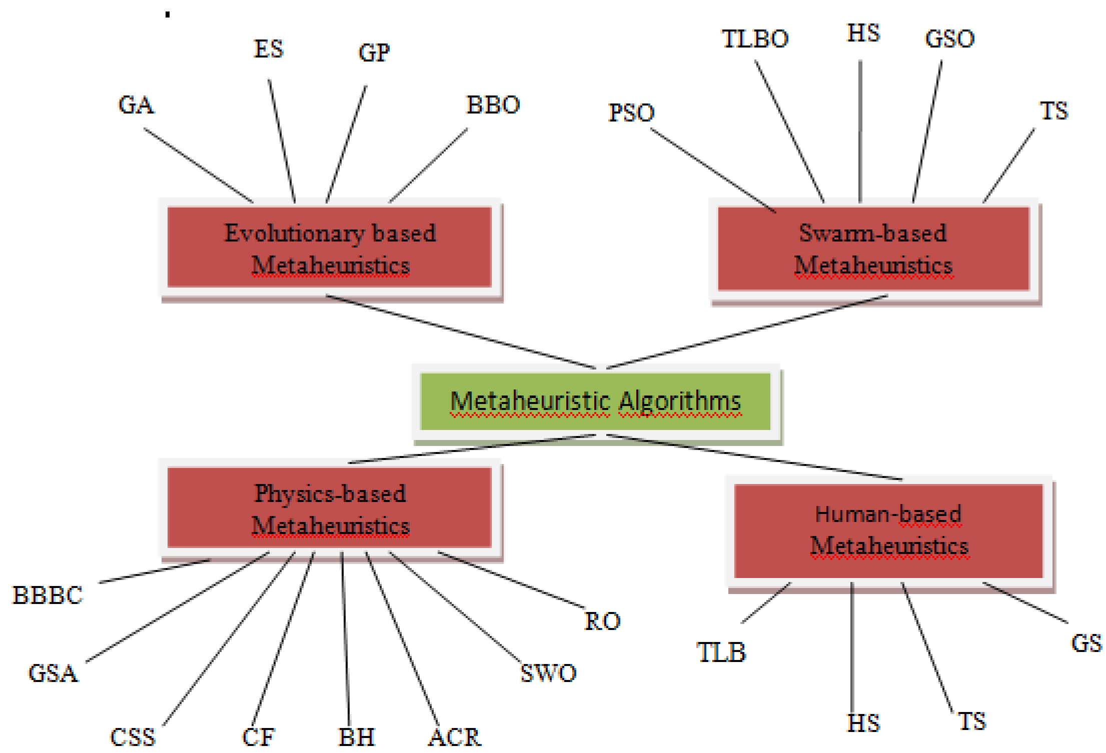

Figure 3.2: Metaheuristic algorithms basic categories

The Evolutionary based metaheuristics include Genetic Algorithm (GA), Evolution Strategy (ES), Genetic Programming (GP), and Biogeography-Based Optimizer (BBO).

The Swarm-based metaheuristics imitate the social behavior of groups of animals, they include Particle Swarm Optimization (PSO), Teaching, Learning Based Optimization (TLBO), Harmony Search (HS), Tabu Search (TS), Group Search Optimizer (GSO) and so on,

The Physics-based metaheuristics are inspired from the physical principles of the real world. They include Big-Bang Big-Crunch (BBBC), Gravitational Search Algorithm (GSA), Charged System Search (CSS), Central Force

Optimization (CFO), Artificial Chemical Reaction Optimization Algorithm (ACROA), Black Hole (BH) algorithm, Ray Optimization (RO) algorithm, Small-World Optimization Algorithm (SWOA).

Human based metaheuristic methods emulate the human behaviors. They include Teaching, Learning Based Optimization (TLBO), Harmony Search (HS), Tabu (Taboo) Search (TS), and Group Search Optimizer (GSO) and others.

3.4 Overview of some Meta-heuristics Based Localization Optimization Algorithms

There exist a number of meta-heuristics that are used for localization optimization in WSNs including Genetic Algorithm (GA), Particle Swarm optimization (PSO), Ant Colony Optimization (ACO), BAT optimization algorithm (BAT), FirefLy Optimization Algorithm (FFA), Flower Pollination Algorithm (FP), Grey Wolf Optimization algorithm (GWO), Artificial Bees Colony Optimization Algorithm (ABC), Fish Swarm Optimization Algorithm (FSA), Monte Carlo Algorithm, Plant Growth Simulation Algorithm, Brain Storming Optimization(BSO), Fruit Fly Meta-heuristic, Teaching Learning Based Optimization (TLBO), Salp Swarm Algorithm (SSA), Biogeographie Based Optimization (BBO) and others. In the following subsections, meta-heuristics based localization optimization stated in the following figure are surveyed.

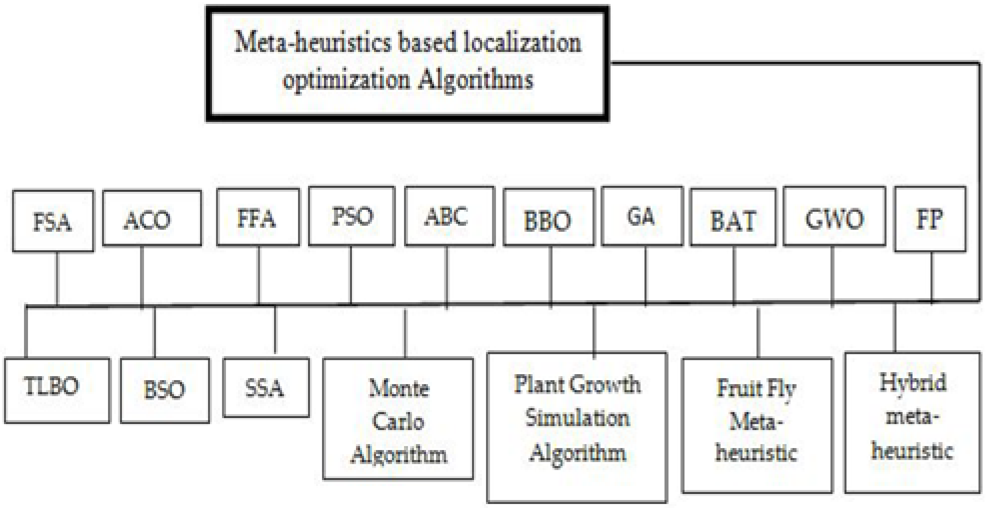

Figure 3.3: Metaheuristics based localization optimization examples [95].

3.4.1 PSO Based Localization Optimization

PSO is a swarm intelligence algorithm, it was developed by Eberhart and Kennedy in 1995 [40]. This algorithm is inspired from the behavior of birds flocking [36] where each bird or particle moves in a population looking for the best solution [41] based on its own experience and the experience of other particles. The PSO algorithm can find the optimal solution through an iterative process [95]: In the first stage PSO randomly generates a set of particles in the search space (initial population). Each particle has an initial position and velocity. In each generation, a particle evaluates its fitness (solution) using an objective function. It updates its position and velocity based on its present best solution (Pbest) and the best solution of the population (Gbest).

Different PSO based localization optimization methods are surveyed here:

1. Maneesha V Ramesh, Divya P. L et all. In "A Swarm Intelligence Based Distributed Localization Technique for Wireless Sensor Network"[27]:

An energy efficient distributed localization technique is proposed in this paper. After a comparison study of energy of processing and transmission in a wireless node, conclusion made of this study is that transmission process consumes more than processing. This article studied the localization problem using two PSO variants: PSO and Comprehensive Learning PSO (CLPSO). Simulation results showed that in both PSO and CLPSO based localization, the number of nodes localized increases as the number of iteration increases. Further PSO based localization performs better in terms of fast convergence than CLPSO but this later is more accurate. Considering that solution quality is more important than fast convergence in localization. Authors concluded that CLPSO is the optimal algorithm for localization in more complex WSNs deployment circumstances.

2. Ziwen Sun, Li Tao, Xinyu Wang, and Zhiping Zhou. In "Localization Algorithm in Wireless Sensor Networks Based on Multiobjective Particle Swarm Optimization" [42]:

   The localization optimization problem is addressed in this article by using a multi objective particle swarm optimization algorithm (MOPSOLA). In this algorithm, estimating unknown nodes coordinates can be achieved by optimizing two objective functions. The first objective function [41] consists of the difference between the real and measured distance between two nodes with introducing RSSI to obtain a ranging distance. The second objective function consists of the geometric topology constraint. Comparison of the proposed algorithm with existing localization algorithms through simulation showed that this later improves localization accuracy and coverage rate.

3. Abdulraqeb Alhammadi, Fazirulhisyam Hashim, Mohd Fadlee, and

Tareq M. Shami. In " An Adaptive Localization System Using Particle Swarm Optimization In A Circular Distribution Form " [26]:

In this work, a new algorithm using PSO for indoor localization is introduced. This algorithm used PSO to estimate the user location relying on the condition that a number of Access Points (AP) with known coordinates are deployed in the indoor environment. The proposed algorithm, first calculates the distance between the target and each AP using RSSI and chooses the AP that achieves the highest RSSI which has the minimum measurement distance error . Second, it generates N particles in a circular distribution around the selected AP. Each particle represents position and likely to be a target. The particle which has correct distances from all AP is selected as the target. The simulation results using four PSO variants showed the proposed method using Self-Organizing Hierarchical PSO with Time Acceleration Coefficients (HPSO-TVAC) variant achieves very low distance error compared with the remaining three PSO variants named Standard PSO (SPSO), Linearly Decreasing Inertia Weight PSO (LDIW-PSO), Self-Organizing Hierarchical PSO with Time Acceleration Coefficients (HPSO-TVAC), and Constriction Factor PSO (CFPSO).

4. Gaurav Sharma, Manjeet Kharub et all. In "Particle Swarm Based Node Localization in Wireless Sensor Networks" [40]:

In this article, authors proposed PSO-IDV algorithm. In this algorithm, PSO is used to improve the accuracy of DV-HOP range free algorithm. First, calculated distance is modified by adding a correction factor to the average hop size of the anchor node, this correction factor based on the difference between the real distance between two anchor nodes calculated by their known coordinates and the distance between two anchor nodes calculated according to DV-HOP rules. Simulation results showed that this algorithm is simple, efficient and more accurate than DV-Hop and DV-Hop based on Genetic Algorithm (GADV-Hop) algorithms.

5. Po-Jen Chuang and Cheng-Pei Wu.In "An Effective PSO-based Node Localization Scheme for Wireless Sensor Networks" [58]:

   Generally, range-based localization schemes use trilateration or multilateration algorithms to calculate the position of unknown node with sufficient anchor nodes in its neighborhood. In order to reduce the hardware cost, iterative multilateration is used. These schemes are unable to locate unknown nodes with insufficient anchor nodes. Further, the iterative process may leads to error accumulation. For improvement, authors present a new localization scheme in this article. This scheme aims to improve localization success ratios by using the location data of remote anchors to calculate the locations of unknown nodes with insufficient neighboring anchor nodes. In this algorithm, the PSO is used to increase the localization accuracy, and the DV-Distance approach is used to improve the success ratio of localization. Simulation results showed that the proposed algorithm performs better than some existing same kind of localization algorithms in increasing the localization success ratios or in reducing localization errors at minimum cost.

3.4.2 GA Based Localization Optimization

GA is a meta-heuristic inspired from the Darwinian principle of biological evolution [18]. It's an iterative algorithm. In the first iteration, GA generates a random population. During each iteration step a new population is created by applying genetic operators which are: selection, crossover and mutation

[28]. Different GA based localization optimization methods are surveyed here:

1. Penghong Wang, Fei Xue , Hangjuan Li, Zhihua Cui, Liping Xie, and Jinjun Chen. In "A Multi-Objective DV-Hop Localization Algorithm Based on NSGA-II in Internet of Things"[53]:

   In this paper, a new multi-objective DV-Hop localization algorithm based on a Non-dominated Sorting Genetic Algorithm II (NSGA-II) is proposed. This algorithm is named NSGA-II-DV-Hop. The proposed algorithm adopted a new multi-objective model and used an improved constraint strategy based on all beacon nodes to improve the DV-Hop localization accuracy. Simulation results using four different networks topologies, including the Random, C-shaped random, O-shaped random, and X-shaped random demonstrated that the enhanced localization algorithm performs better than other existing localization algorithms.

2. Zaineb Liouane, Tayeb Lemlouma, Philippe Roose, Frédéric Weis, and Messaoud Hassani. In "A Genetic—based Localization Algorithm for Elderly People in Smart Cities "[43]:

   Localizing aging persons when they outside is one of the important issues in supervision and assistance systems for elderly in smart cities. The objective of the work presented in this paper is to provide an efficient tool for localizing old peoples when it's necessary and in real time. In this paper, authors proposed to use Wireless Body Area Networks (WBAN). This technology used for health monitoring permits to place a number of sensors in the body of the person to check his health state. The proposed localization approach consists of an improved DV-HOP algorithm based on GA to improve the localization accuracy. The GA is used in anchor selection step. Simulation results confirmed that the proposed algorithm performs better than the classic DV-HOP.

3. Vincent Tam, King-Yip Cheng and King-Shan Lui. In "Using Micro-Genetic Algorithms to Improve Localization in Wireless Sensor Networks "[57]:

   Ad-hoc Positioning System (APS) is one of the popular localization algorithms. This algorithm use triangulation that requires only positions of three anchors to compute the unknown node location. If an unknown node receives more than three anchor nodes positions, it can use all anchor nodes positions or select only three to calculate its position. This work studied the effect of choosing different anchor nodes in the localization and proposed an improved APS based on Adapted Micro Genetic algorithm that allow selecting the most appropriates anchor nodes (three or more) among all possible combinations of three anchor nodes. Results obtained through simulation confirmed the efficiency of the proposed algorithm compared with classic APS and the improved APS algorithm called APS (near-3) [19] previously proposed by the same authors that always selects the nearest 3 anchors positions to calculate unknown node position.

4. Kapil Uraiya , and Dilip Kumar Gandhi. In "Genetic Algorithm for Wireless Sensor Network With Localization Based Techniques "[32]:

   Range based techniques based on the ranging measurement distances to estimate the unknown nodes positions. In this paper, authors focus on these techniques and presented a combined RSS and AOA based on GA for estimating unknown nodes positions more accurately. After estimating its distances from all anchor nodes by using RSSI, a sensor node starts finding angle of arrival from each anchor node. Then the sensor node uses the GA to find its coordinates. Simulation results for different scenarios showed that the proposed algorithm can estimate the unknown sensor position with less anchor nodes and more accuracy. This work also concluded that using more than three anchor nodes increase the time without improving localization accuracy.

5. N. Jiang, S. Ji, Y. Guo, and Y. He. In "Localization of Wireless Sensor Network Based on Genetic Algorithm "[33]:

   WSNs usually estimate the location of the unknown node based on the measured distance between this node and its neighboring anchor nodes. When an unknown node fails to find sufficient anchor nodes in its neighborhood, its location can't be estimated. This paper proposed a new localization approach based on GA. This approach uses a new method to approximate the distance between an anchor node and unknown node which is out of anchor node's communication radius. The localization approach proposed in this paper can be visualized to work in two phases: in the first phase, the unknown nodes estimate their distances from anchor nodes either through RSSI if there are sufficient anchor nodes in the neighborhood, or the new method proposed in this paper otherwise. In the second phase, the proposed algorithm uses the GA for the unknown nodes positions estimation. Experimental results on various network topologies showed the proposed approach achieves better results.

3.4.3 ACO Based Localization Optimization

ACO algorithm is inspired from the foraging behavior of real ant colonies [38]. When searching of food, ants deposit the pheromone on the followed path. The pheromone concentration on the path indicates the probability of using this path [37]. After much iteration, the path that has more pheromone is chosen as the optimal path. Different ACO based localization optimization methods are surveyed here:

1. S. Sivakumar, and R. Venkatesan. In "Error Minimization in Localization of Wireless Sensor Networks using Ant Colony Optimization"[21]:

   This paper makes use of ACO algorithm to improve the localization accuracy. Initially, the sensor nodes locations are estimated by using Mobile Anchor Positioning with Mobile and Neighbor (MAP–M&N) algorithm. In this step, unknown nodes calculate their positions using the location information of a mobiles anchor nodes and the location information of neighboring nodes. By using mobiles anchor nodes, the location of each unknown sensor node is approximated to two locations. The sensor node location is further refined by the MAP with Mobile Anchor (MAP–M) to obtain a single position. If a MAP–M fails to determine a single position of some sensor nodes, the method of MAP–M&N is used to overcome this problem. In MAP–M&N the sensor nodes that have already determined their positions start acting like anchor nodes and broadcast their locations to assist other nodes estimating their positions. ACO algorithm is used by taking as input results obtained by MAP–M&N. simulation results confirmed that ACO with MAP-M&N is efficient compared to MAP–M&N algorithm.

2. Fu Qin, Chen Wei, and Liu Kezhong.In "Node Localization with a Mobile Beacon Based on Ant Colony Algorithm in Wireless Sensor Networks"[24]:

   To assist unknown sensor nodes obtain their positions, the localization schemes use either statics or mobiles anchor nodes. Generally, involving more static anchor nodes can increase the localization accuracy but increase also the cost of the entire network. In this paper, the authors proposed a new localization scheme using a mobiles anchor nodes that traverse the wireless network and broadcast virtual beacons contain their positions. The number and the initial distribution of mobile anchor nodes are determined based on equilateral triple optimal coverage, which allow each unknown node obtains sufficient localization information. The ACO algorithm is used to determine the optimal path followed by the mobile anchor. For more improvement in localization accuracy, authors proposed an optimal method to select the optimal set of virtual beacons required for localization. Simulation results confirmed that the proposed scheme improves localization accuracy, reduces the localization cost and saves energy consumption compared to existing schemes.

3. G.Leela Ganapathi1, and M.Madhumathi. In "Location Identification and Tracking of Nodes using ACO Approach"[22]:

   The main purpose of this work is to increase the network lifetime by diminishing the energy consumption of the sensors in a mobile network. To reach this objective, this article proposed a strategy for tracking a moving target in WSNs using mobiles anchors. In the proposed algorithm, the positions of both targets nodes and mobile anchor nodes are estimated first. After, ACO algorithm is used to manage the mobility of anchor nodes by directing it to follow the target node. Experimental results showed that the proposed strategy achieves good tracking performances.

4. Li Jinpeng, and Gao Li.In "The Node Localization Research of the Underground wireless Sensor Networks Based On DV-Hop and Ant Colony Optimization"[33]:

This paper proposed the node localization research of the Underground Wireless Sensor Networks (UWSNs) based on DV-Hop and ACO meta-heuristic. This algorithm is intended to achieve the monitoring and tracking of underground workers to ensure their security and safety. The proposed method based on improved DV-Hop localization algorithm to estimate the distance between unknown nodes and beacon nodes. Then taking three or more beacon nodes to estimate unknown nodes location using the triangular positioning method and through ACO to optimize the error function of triangular positioning which improve localization accuracy. Simulation results showed that the proposed algorithm has higher positioning accuracy compared with traditional DV-Hop localization Algorithm.

5. Yan Hong Lu and Ming Zhang. In "Adaptive Mobile Anchor Localization Algorithm Based On Ant Colony Optimization In Wireless Sensor Networks"[25]:

This article proposed an adaptive mobile anchor localization algorithm based on ant colony optimization in WSNs. This algorithm has three parts. In the first part, authors proposed a model for distributing some virtual anchor nodes in the area in a way that ensures: the coverage of all the area by the signal transmitted by mobile anchor while moving, each unknown node can receive more than three signals from anchor nodes and reduction of anchor nodes transmission signal to save energy. The proposed strategy used in the second part is an improved ACO algorithm, it is used to get the optimal path. Finally, the centroid-weighted algorithm is used to estimate the unknown nodes positions. Simulation results confirmed that the proposed algorithm has higher localization accuracy compared with traditional centroid algorithm and concluded that increasing the number of anchor nodes can decrease the localization error. Further, under the same anchor nodes, the increase of unknown nodes number decreases also the localization error.

3.4.4 ABC Based Localization Optimization

The ABC algorithm is a meta-heuristic approach proposed by Karaboga [61]. The algorithm is inspired from the intelligent foraging behavior of honey bee swarms. This algorithm is simple, robust, and can quickly find the optimal solution [48]. Various ABC based localization optimization methods are surveyed here:

1. Tianfei Chen, and Lijun Sun. in "A Connectivity Weighting DV–Hop Localization Algorithm Using Modified Artificial Bee Colony Optimization"[52]:

   The objective of this article is to improve the localization precision of the traditional DV-hop algorithm by analyzing the reasons of its localization error. In this paper, authors proposed a connectivity weighting DV–Hop localization algorithm using modified ABC optimization algorithm. In the proposed algorithm, the Average Hop Distance (AHD) of anchor nodes is calculated based on the minimum mean squared distance error between the estimated distances of anchor nodes and the actual distances from them. The AHD of unknown nodes is calculated based on the influence of local network properties of anchor nodes and the distances between anchor nodes and unknown nodes. Finally the multilateral localization is optimized by a modified ABC algorithm. Simulation results showed that the modified ABC algorithm can reduce the probability of premature convergence and improve the localization accuracy.

2. Wanli Zhang, Xiaoying Yang and Qixiang Song. In "Improved DV-Hop Algorithm Based on Artificial Bee Colony"[59]:

A new Artificial Bee Colony DV-Hop (ABCDV-Hop) algorithm is proposed in this article, in order to reduce the node localization error of DV-Hop algorithm in WSNs. The proposed algorithm is an improved version of traditional DV-HOP algorithm, in which the average distance per hop of anchor nodes is calculated by ABC algorithm to make it close to the optimal value. Simulation results showed that the improved algorithm has better localization accuracy than traditional DV-Hop.

3. Vikas Gupta, and Brahmjit Singh. In "Centroid Based Localization Utilizing Artificial Bee Colony Algorithm"[60]:

The centroid based localization algorithm (CLA) is one of the most used algorithms for node localization in WSNs. This algorithm suffers from large localization error. In this article, the CLA is evaluated in terms of localization error applying ABC algorithm and compared with other popular techniques namely PSO and evolutionary algorithms based differential evolution (DE) on basic centroid localization algorithm. Simulation results showed that the ABC and DE based CLA have best localization accuracy compared to basic and PSO based schemes but DE based localization algorithm has high computation time compared to others.

4. R K Jena. In "Artificial Bee Colony Algorithm based Multi- Objective Node Placement for Wireless Sensor Network"[61]:

This article proposed a multi-objective algorithm based on ABC (ABCMO) for WSNs localization. The fitness function of this algorithm consists of optimizing many parameters including sensor deployment parameters, connectivity parameters and energy consumption parameters. The ABCMO use pareto concept and external archive strategy to make the algorithm converge to the optimal pareto front and use comprehensive learning strategy to guarantee the diversity of the population. The results obtained through simulation demonstrated that the proposed algorithm outperforms other widely used techniques including PSO and ACO based approaches.

5. S.Sivakumar. In "Artificial Bee Colony algorithm for Localization in Wireless Sensor Networks"[62]:

   In this paper, MAP-M&N discussed in [27, 29, 69] is used for nodes localization in WSNs. In order to improve the positioning accuracy of this algorithm, the sensor nodes use the location information of mobiles anchor nodes and the location packets of neighboring nodes. The ABC algorithm is incorporated with MAP–M&N to further increase its accuracy in localizing the sensor nodes. In order to evaluate the performance of the proposed algorithm using ABC, it is compared with MAP–M&N algorithm using Root Mean Square Error (RMSE) as performance metric. Simulation results showed that ABC approach used with MAP–M&N is better than MAP–M&N approach for localization in terms of localization accuracy.

3.4.5 FFA Based Localization Optimization

FFA algorithm is a meta-heuristic developed in 2007 by Yang at Cambridge university [65], this meta-heuristic is inspired from behavior of fireflies insects which emit regular light flashes to attract others for mating. Various FFA based localization optimization methods are surveyed here:

1. Lovepreet Kaur, Ameeta Seehra and Daljit Singh. In "Node Localization in Wireless Sensor Network using Firefly Algorithm"[63]:

   In order to improve the localization accuracy and the computing time, the FFA is used for nodes localization in this article. The fitness function of localization in the proposed algorithm consists of minimizing the difference between the calculated distance between anchor node and proximate unknown nodes and the actual distance between them. The performance of the proposed algorithm is evaluated by considering the localization error, the number of localized nodes and the computation time.

2. Trong-The Nguyen, Jeng-Shyang Pan, Shu-Chuan Chu, John F. Roddick, and Thi-Kien Dao. In "Optimization Localization in Wireless Sensor Network Based on Multi-Objective Firefly Algorithm"[64]:

   In this article, a multi-objective model is proposed for localization in WSNs. The objective functions included the distances constraint and the topological constraint. The Multi-objective Firefly Algorithm (MFA) is used to achieve the optimal solution. The proposed algorithm optimizes the distances constraint to make the calculated coordinates close to the real values, and optimizes the topology constraint to make the network topology unique. Simulation results showed that the proposed technique is better than other techniques for localization in terms of localization accuracy and convergence rate.

3. Basem Amer, and Aboelmagd Noureldin. In "RSS-Based Indoor Positioning Utilizing FireFly Algorithm in Wireless Sensor Networks"[65]:

   This article proposed a localization system for indoor environments. The proposed technique utilizes RSS technology with Barometers sensor and FFA to determine nodes locations. In order to estimate their distances from anchor nodes, the mobile node sends message to all anchor nodes to obtain signal strength measurements (RSS). Kalman Filter (KF) is used to remove the noise from the measurements of barometers sensor. Finally, the FFA is used to find the optimal positions of the mobile node. Simulation results showed that the proposed algorithm can efficiently localize mobile nodes in indoor environment.

4. S. Sivakumar, and C.Bharathi Priya. In "Jumper Fire Fly Optimization Algorithm for Mobile Anchor Based Localization"[66]:

   The main objective of the proposed algorithm in this article is to increase the localization accuracy. For this, a new localization algorithm namely Jumper Firefly Optimization Algorithm with Mobile Anchor Positioning algorithm (JFA–MAP) is proposed. In this algorithm, Jumper Firefly Optimization Algorithm is used over the results of MAP–M&N previously discussed in [?, 18, 58, 51]. Simulation results showed that JFA–MAP can reduce the localization error compared with MAP–M&N algorithm.

5. Van-Oanh Sai, Chin-Shiuh Shieh, Trong-The Nguyen, Yuh-Chung Lin, Mong-Fong Horng, and Quang-Duy Le. In "Parallel Firefly Algorithm for Localization Algorithm in Wireless Sensor Network"[67]:

   This paper proposed a new localization algorithm based on RSS technology and Parallel Firefly Algorithm. The parallel FFA algorithm is developed based on original FFA algorithm. The population in FFA is divided into subpopulations to creating some groups. These subgroups cooperate to find the optimal locations of the nodes in the WSNs. Simulation results showed that the proposed parallel FFA is efficient in reducing the localization error than PSO, GA and the original FFA.

3.4.6 Hybrid Metaheuristics Based Localization Optimization

Many localization algorithms used hybrid meta-heuristics for obtaining nodes positions in WSNs. we will survey in this subsection a set of hybrid meta–heuristics used in localization optimization.

1. P. SrideviPonmalar, V. Jawahar Senthil Kumar, and R. Harikrishnan. In "Hybrid Firefly Variants Algorithm for Localization Optimization in WSN"[68]:

   In this article, three new hybrids meta-heuristic algorithms are proposed for node localization in WSNs. In Genetic Algorithm Firefly Localization algorithm (GA-FFLA), the FFA is combined with GA. The FFA is combined with differential evolution (DE) in the differential evolution Firefly Localization Algorithm (DE-FFLA). In the third algorithm namely Particle Swarm Optimization Firefly Localization Algorithm (PSO-FFLA), FFA is hybrid with PSO. Performance of the proposed hybrid algorithms are evaluated by comparing them with each others.

2. Shanthi M. B., and Dinesh K. Anvekar.In "Secure Localization in UWSN using Combined Approach of PSO and GD Methods"[55]:

   This paper proposed a new algorithm for node localization in Under Water Wireless Sensor Networks (UWSN). The proposed algorithm combines PSO with Gradient-Descent (GD) optimization algorithm. Firstly, the GD optimization algorithm is combined with Maximum Likelihood (ML) method to determine the malicious nodes in the network. The main objective of this step is to ensure the localization security by avoiding the participation of malicious nodes in the localization process. After, the PSO algorithm is used to determine optimal positions of unknown nodes. Simulation results showed that the proposed algorithm is better than PSO and GD when there are malicious nodes in the network.

3. Taner Tuncer. In "Intelligent Centroid Localization Based on Fuzzy Logic and Genetic Algorithm"[70]:

   In order to reduce the error of the centroid localization algorithm in determining the nodes locations in WSNs, this paper proposed to use the fuzzy logic and GA with original centroid localization algorithm. In the proposed algorithm named Intelligent Centroid Localization (ICL) Method, fuzzy logic is used to assign weigh values for anchor nodes by considering RSSI values measured by these anchor nodes. Fuzzy logic system aims to define correctly the relationship between RSSI values and weighs in order to increase the effect of high RSSI values. The outputs of fuzzy logic system are used by the GA to determine optimal locations of nodes. Simulation results showed that the ICL can reduce the localization error compared with Centroid Localization method and Approximate Point In Triangulation (APIT) algorithm.

4. SrideviPonmalar P, Jawahar Senthil Kumar V, and Harikrishnan R. In "Bat-Firefly Localization Algorithm for Wireless Sensor Networks"[71]:

   This article proposed Bat-Firefly localization Algorithm (BF-LA). In this algorithm BAT algorithm and FFA collaborate to solve localization problem in WSNs. BAT algorithm is executed to estimate the coordinate of unknown node in the first stage of the proposed algorithm. Then, the fitness value of best solution of bat is considered as initial population of fireflies. Simulation results showed that the proposed hybrid BF-LA can achieve good accuracy.

5. S.R.Sujatha , and M.Siddappa. In "Node Localization Method for Wireless Sensor Networks Based on Hybrid Optimization of Particle Swarm Optimization and Differential Evolution"[18]:

   In this work, BAT algorithm is combined with PSO algorithm to reduce the error of localization in WSNs. In the proposed algorithm called BF-LA, the initial population is divided into two populations and PSO and BAT algorithms run simultaneously. Select the better value between Gbest (PSO) and Gbest (DE) as initial value in PSO and DE in the next step of the algorithm. The optimal location is the best value in all groups at the end of the algorithm. Performance evaluation proved that the proposed algorithm provided better results.

3.4.7 Other Metaheuristics based Localization Optimization

In addition to the meta-heuristics discussed in this article, there exit other meta-heuristics which are applied to solve the WSNs localization problem. Some of these meta-heuristics based localization optimization methods are surveyed here:

1. S. Sivakumar. In "Error Minimization in Localization of Wireless Sensor Networks using Fish Swarm Optimization Algorithm"[44]:

   In this paper, a meta–heuristic called Fish Swarm Optimization Algorithm is used with MAP–M&N algorithm to ovecome the localization problem. The proposed algorithm use MAP–M&N algorithm in which a mobile anchor node fited with GPS travers the network and broadcat its coordinates to assist unknown nodes estimate their positions. Fish Swarm Optimization Algorithm is used with this algorithm to calculate the locations of sensor nodes more accurately by considering Root Mean Square Error as the performance evaluation metric. Compared with MAP–M&N, MAP–M&N with Fish Swarm Optimization Algorithm can significantly reduce the localization error.

2. Anil Kumar. In "Optimized Distributed Range-Based Node Localization in Wireless Sensor Networks"[45]:

   To find out the 3D coordinates of unknown sensor nodes deployed in anisotropic networks, this paper proposed a range based 3D node localization algorithm which use a BBO algorithm. Simulation results showed that the accuracy and the number of localized nodes of the proposed algorithm are high than those of PSO algorithm.

3. A. Kurecka, J. Konecny1, M. Prauzek and J. KozioreK. In "Monte Carlo Based Wireless Node Localization"[46]:

   Wireless node Monte Carlo Localization algorithm (WNMCL) is proposed in this paper. In this algorithm, only one mobile anchor node traverses the network and collect RSS signal from unknown nodes. The distances between unknown nodes and anchor node are estimated by the path loss model. Finally Monte Carlo Localization algorithm is used to find out unknown nodes positions. The proposed algorithm is tested by taking into consideration the accuracy and the localization speed.

4. Gaurav Sharma1 and Manjeet Kharub. In "Enhanced Range Free Localization in Wireless Sensor Networks"[47]:

In order to enhance the localization accuracy in range free localization algorithms, this paper proposed an improved DV-Hop algorithm based on TLBO algorithm (IDV-Hop based on TLBO). In this algorithm, the traditional DV-Hop algorithm is modified by adding a correction factor to the average hop size of the anchor node. To more improve the localization accuracy, TLBO algorithm is used. Simulation results showed that the IDV-Hop based on TLBO locates unknown nodes more accurately than traditional DV-Hop, DV-Hop using GA and DV-Hop using PSO algorithm.

5. Huthaifa M. Kanoosh, Essam Halim Houssein, and Mazen M. Selim. In "Salp Swarm Algorithm for Node Localization in Wireless Sensor Networks"[39]:

   This paper proposed a WSNs localization algorithm based on a recent developed metaheuristic named Salp Swarm Algorithm (SSA). The proposed algorithm estimate unknown nodes positions through iterative process using location information of three or more anchor nodes. In each iteration step, localized nodes will act as anchor nodes to increase the number of localized nodes. Simulation results showed that SSA based WSNs localization performs better than PSO, Butterfly optimization algorithm (BOA), FFA and GWO in terms of localization accuracy and execution time.

6. Chengpei Tang, Ruiqi Liu, Jiangqun Ni . In "A Novel Wireless Sensor Network Localization Approach: Localization based on Plant Growth Simulation Algorithm"[49]:

   This article proposed an enhanced Plant Growth Simulation Algorithm (PGSA) for localization in WSNs. First, the distances between anchor nodes and unknown nodes are calculated by using one of ranging techniques. Next, to locate unknown node, the objective function which to be optimized consists of a difference between estimated and actual distances. Simulation results showed that the proposed algorithm is better than simulated annealing algorithm in terms of computing speed and localization accuracy.

7. Chin-Shiuh Shieh, Van-Oanh Sai, Tsair-Fwu Lee, and Quang-Duy Le. In "Node Localization in WSN using Heuristic Optimization Approaches"[52]:

   In this article, the localization problem is overcome by using some bio mimetic algorithms such as GA, PSO, GWO, FFA, and BSO. A comparative study between these meta-heuristics is done in the first part of this paper. Next, these algorithms are applied for localization in WSNs, and their performances are evaluated in terms of the number of nodes can be localized and the execution time. This article proposed also a new method to locate unknown nodes with only two neighboring anchor nodes which can increase the number of localized nodes.

8. Seddik Rabhi, and Fouzi Semchedine. In "Localization in Wireless Sensor Networks Using DV-Hop Algorithm and Fruit Fly Meta-heuristic"[58]:

   In this article, an improved algorithm for localization in WSNs is proposed. In this algorithm, DV-Hop localization algorithm is combined with the Fruit Fly meta-heuristic. Firstly, the unknown nodes locations are estimated by using DV-Hop localization algorithm. These locations are considered as initial locations which are used after by the Fruit Fly meta-heuristic (FOA) to minimize the localization error. Simulation results showed that the improved algorithm is better in term of localization accuracy than classical DV-Hop localization algorithm.

9. Ranjit Kaur, and Sankalap Arora. In "Nature Inspired Range Based Wireless Sensor Node Localization Algorithms"[36]:

   In this article, the performances of some bio inspired algorithms namely FP, FFA, PSO and GWO are analyzed for localization in WSNs. The initial population is sated as main objective of localization using these bio inspired algorithms is to localize the maximum number of sensor nodes by using the location information of anchor nodes. When an unknown node detects three or more anchor nodes, it calculates the centroid of their locations to initialize the population. After, each optimization algorithm is executed independently by minimizing the objective function. Simulation results showed that the Flower Pollination Algorithm is more efficient than other algorithms.

3.4.8 Comparison and Discussion

The meta-heuristics based localization optimization algorithms reviewed in this chapter are summarized in table 4.1. These algorithms differ in many parameters including the meta-heuristic optimization algorithm parameters, the network scenario parameters and the performance evaluation criteria parameters.

Considering the meta-heuristic parameters, the localization optimization algorithms can use one or more of the meta-heuristics discussed in this paper. These mea-heuristics can optimize either a single or a multi-objective function.

For the network scenario, the localization optimization algorithms can be used for estimating the 2D or 3D coordinates in static or in dynamic network. In addition, these algorithms can use a static or a dynamic anchor nodes or the both to locate unknown nodes.

To evaluate their performance, localization optimization algorithms can test one or many parameters such as accuracy, convergence rate, energy consump-

tion and the number of localized nodes.
Results obtained by each algorithm are given in the last column of the table1, where the localization error(LE) reflect the accuracy of the algorithm, the computational time(CP) reflect the convergence rate,the success ratio represents the percentage of localized nodes and EC represents the energy consumption of nodes.

Based on the summary made in the table 1, we can conclude that the majority of the localization optimization algorithms based on meta-heuristics focus on searching to estimate the 2D positions in the static networks such as the algorithms proposed in [42, 57, 32, 23, 61, 64, 48].
These algorithms use in the most case a static anchor nodes and a single objective function like the algorithms proposed in [26, 69, 29, 60, 71, 18].

In addition, all the meta-heuristics based localization optimization consider a set of performance parameters and the most of these algorithms use the accuracy as performance evaluation criteria. For example, M. V Ramesh et al. In [27] evaluate their algorithm in terms of localization accuracy and convergence rate, L. Kaur et al. In [63] use the localization accuracy, the convergence rate and the number of localized nodes as performance evaluation criteria. Shanthi M. B et al. In [55] considers the localization accuracy, the convergence rate, the energy consumption and the number of localized nodes as the performance evaluation criteria.

To summarize, there is no meta-heuristic that offer best performance evaluation criteria than others, more especially, no meta-heuristic can be determined as best meta-heuristic as performance evaluation criteria. Also, we can' t determine that exist a meta-heuristic suitable for a type of network than other.

Table 3.1: Summary of different meta-heuristics used on WSNs localization optimization

Reference	Optimization Algorithm Parameters			Network Scenario						Performance Evaluation Criteria				Results
	Meta-heuristic used	Single Objective Function	Multi Objective Function	2D	3D	Dynamic Network	Statiic Network	Dynamic Anchors	Static Anchors	Localization accuracy	Convergence Rate	Energy Consumption	Number of localized Nodes	
[38](2006)	PSO,CLPSO	√		√			√		√	√	√			PSO:LE=0.5486m, CT=73.8721s, CLPSO:LE=0.0551m, CT= 975.0115 s
[63](2015)	PSO		√	√			√		√	√	√			LE=9.25%
[37](2016)	HPSO-TVAC, SPSO, LDIW PSO, HPSO-TVAC, CF-PSO	√		√		√			√	√	√			SPSO:LE=1.32m, LDIW-PSO:LE=0.67m, CF-PSP:LE=0.40m, HPSO-TVAC:LE=0.19m
[80](2008)	PSO	√		√			√		√	√			√	LE=30%,SR=99%
[51](2017)	PSO	√		√			√		√	√				LE=9%
[54](2016)	GA	√		√		√			√	√				LE=0.0185m
[68](2006)		√		√			√		√	√				LE=0.314m
[43](2014)			√	√			√		√	√	√			LE=1.5357%
[44](2013)		√		√			√		√	√				LE=15%
[45](2019)			√	√			√		√	√				LE=22.09%
[32](2016)	ACO			√			√	√		√				LE=8.72m
[35](2010)				√			√	√		√				LE=0.196m
[33](2014)				√		√		√				√		The energy consumption of nodes is decreased by the algorithm
[34](2011)				√			√		√	√				LE=18%
[36](2014)				√			√	√	√	√				LE=15%
[70](2015)	ABC	√		√			√		√	√				LE=25%
[71](2019)		√		√			√		√	√	√			LE=0.0251m
[63](2019)		√		√			√		√	√	√			LE=13%
[72](2014)			√	√			√		√		√	√	√	CT=0.5s

Table 3.1: Continued

Reference	Optimization Algorithm Parameters			Network Scenario						Performance Evaluation Criteria				Results
	Meta-heuristic used	Single Objective Function	Multi Objective Function	2D	3D	Dynamic Network	Statiic Network	Dynamic Anchors	Static Anchors	Localization accuracy	Convergence Rate	Energy Consumption	Number of localized Nodes	
[73](2017)		✓		✓		✓		✓		✓				LE=9.33s
[74](2018)	FFA	✓		✓			✓		✓	✓	✓		✓	LE=15.5%,CT=0.8s
[75](2016)			✓	✓			✓		✓	✓				LE=16.5%
[76](2016)		✓		✓		✓			✓	✓				LE=2.8m
[87](2019)		✓		✓			✓	✓		✓				LE=2.76m
[78](2015)		✓		✓			✓		✓	✓	✓		✓	LE= 0.0015m,SR= 100%
[66](2019)	PSO, GD	✓		✓			✓		✓	✓	✓	✓	✓	By increasing the number of attackers,delay from 0.0040s to .0043s, Energy consumption varies from 1065.11J to 1582.50J
[79](2017)	FFA, GA,PSO,DE	✓		✓			✓		✓	✓	✓			GA-FFLA outperform DE-FFLA and PSO-FFLA in term of accuracy and Time complexity
[81](2017)	GA	✓		✓			✓		✓	✓				LE=0.986 m
[82](2017)	BAt, FFA	✓		✓			✓		✓	✓	✓			LE=25%, CT=1.234s
[29](2017)	PSO, DE	✓		✓			✓		✓	✓	✓			The hybride method proposed obtain better results
[55](2017)	FSA	✓		✓			✓	✓		✓				LE=6.95m
[56](2013)	BBO	✓			✓		✓		✓	✓	✓		✓	LE=0.00264m,SR= 99%,CT=52.46s
[57](2014)	WNMCL	✓		✓			✓	✓		✓	✓			The time complexity is low
[58](2014)	TLBO	✓		✓			✓		✓	✓	✓			LE=27%,CT=15.02 s
[50](2019)	SSA	✓		✓			✓		✓	✓	✓		✓	LE=0.504m,SR=100%,CT=1.37s
[60](2013)	PGSA	✓		✓			✓			✓	✓			LE=0.000023904m,CT=2.3394s

Table 3.1: Continued

Reference	Optimization Algorithm Parameters			Network Scenario						Performance Evaluation Criteria				Results
	Meta-heuristic used	Single Objective Function	Multi Objective Function	2D	3D	Dynamic Network	Static Network	Dynamic Anchors	Static Anchors	Localization accuracy	Convergence Rate	Energy Consumption	Number of localized Nodes	
[65](2017)	GA, PSO, GWO, FA, BSO	√		√			√		√	√	√		√	LE=95%, GA obtained the best accuracy compared to other techniques
[69](2019)	FOA	√		√			√		√	√				LE=3.5504m
[47](2017)	FPA, FFA, PSO, GWO	√		√			√		√	√	√		√	FPA:LE=0.28374m,SR=95.5%, CT=0.767 PSO:LE=0.584231,SR=93%, CT=0.743s, GWO:LE=0.802848m,SR=95%, CT=0.83s

3.5 Conclusion

As exact location information is very important for the WSNs performance of many applications, researchers have proposed different schemes to give the most accurate locations of sensor nodes. In this chapter, we proposed a new taxonomy of the algorithms used for localization optimization. In this taxonomy, localization optimization algorithms are classified as mobile anchor based localization optimization ,machine learning based localization optimization, mathematical models based localization optimization and meta-heuristics based localization optimization. These later are one of the most used algorithms for localization optimization in WSNs. They are reviewed in this chapter . We concluded with a table which summarizes the different algorithms discussed in this chapter and a discussion of them in terms of performance parameters like accuracy, convergence rate, energy consumption and the number of localized nodes.

CHAPTER 4

LOCALIZATION OPTIMIZATION IN WSNS BY USING CAT SWARM AND SOCIAL SPIDER METAHEURISTIC ALGORITHMS

4.1 Introduction

Traditional localization algorithms suffer from the high error of localization, therefore, they need to be enhanced. This chapter proposed a new localization algorithms based on metaheuristics. The first algorithm namely Centroid Localization Algorithm is based on Social Spider Optimization Algorithm (CLA-SSO). This algorithm uses the Social Spider Optimization metaheuristic (SSO) to improve the localization of the basic Centroide Localization Algorithm (CLA) which is a range free localization algorithm. The second proposed algorithm called Centroid Localization Algorithm based on Cat Swarm Optimization Algorithm (CLA-CSO). In this method, the Cat Swarm Optimization algorithm is used to optimize the localization of traditional CLA. In addition, simulation results are shown and discussed for each contribution.

4.2 Social Spider Optimization Meta-heuristic for Node Localization Optimization in WSNs

4.2.1 Social Spider Optimization Algorithm Principe

SSO [87] is a novel meta-heuristic inspired from the cooperative behavior of social spiders witch live in groups by forming colonies. Members of social spider colony can be classified based on their gender into two groups: Females and Males spiders. Female spiders represent the largest proportion in the spider colony which may reach up 90% of the total number (Ns) of the colony members. Male spiders can in turn be dominant or non-dominant, where the dominant spiders have best fitness than non-dominant spiders.

To resolve an optimization problem, the original SSO algorithm follows many steps as described below:

1. Initialize the N_s spiders of the initial population randomly as follows: Generate randomly N_f female spiders between 65% and 90% and N_m male spiders using the following equations:

$$N_f = Fix[(0.9 - rand * 0.25)] \tag{4.1}$$

   Where:Fix transforms the real number to an integer number and rand a random number within the range[0,1].
   the number of male spiders is calculated as follows:

$$N_m = N_s - N_f \tag{4.2}$$

2. Initialize randomly each female and each male spider as follows:

$$f_{i,j}^{initial} = p_j^{min} + rand(0,1) * (p_j^{max} - p_j^{min}) \tag{4.3}$$

$$m_{k,j}^{initial} = p_j^{min} + rand(0,1) * (p_j^{max} - p_j^{min}) \tag{4.4}$$

3. Calculate the weight of each spider depending on its fitness value by using the equation 7.

$$w_i = \frac{fitness(s_i) - worst_s}{best_s - worst_s} \tag{4.5}$$

   Where: $fitness(s_i)$ is the fitness value of of the spider i, $best_s$ and $worst_s$ represent respectively the best and the worst fitness among the population S. This weight represents the quality of solution obtained by the spider. The spider with the highest weigh is the fittest member.

4. Calculate vibrations received by each spider from different spiders in the colony depending on the weight and the distance of the spider which

has transmitted them according to the following equation.

$$V_{ij} = W_j * e^{-d_{ij}^2} \tag{4.6}$$

Where: W_j is the weight of the spider S_j and d_{ij}^2 is the euclidean distance between the spider S_i and the spider S_j. In fact, each spider receives three types of vibrations:
a) Vibrations $V_i cb_j$ are received by the spider S_i from the closest spider S_j which has more weight $(W_j > W_i)$.
b) Vibrations $V_i b_j$ are received by the spider S_i from the fittest spider S_i who has the biggest weight of the whole population (the fittest spider).
c)Vibrations $V_i f_j$ are received by the spider S_i from the nearest female spider S_j.

5. Update the position of each spider colony member depending on its gender by using different cooperative operators as mentioned below:
a) Female cooperative operator: Female spiders present an attraction or repulsion movement over other spiders in the colony as modeled in the following equation:

$$f_i^{(t+1)} = \begin{cases} f_i^t + \alpha.V_i cb_j(S_c - f_i^t) + \beta.V_i b_j(S_b - f_i^t) + \varphi(rand - \frac{1}{2}) \\ ifp < PF \\ f_i^t - \alpha.V_i cb_j(S_c - f_i^t) - \beta.V_i b_j(S_b - f_i^t) + \varphi(rand - \frac{1}{2}) \\ ifp > PF \end{cases} \tag{4.7}$$

Where: S_c is the nearest spider holding higher weight, S_b is the fittest spider, P is a random number generated within the range $[0, 1]$ and PF a predefined function.
b) Male cooperative operator: Male spiders can be dominant or non dominant, then the male group is divided into dominant male(d) and non dominant male (Nd) spider based on the solution quality of the male member spider where the dominant spiders have best fitness

than non-dominant spiders.

$$m_i^{(t+1)} = \begin{cases} male(d), W_i > median(W) \\ male(Nd), W_i < median(W) \end{cases} \tag{4.8}$$

Where median is the spider situated in the middle of the male population in regard of its weight.
Dominant male spiders are attracted to the nearest female spider of the colony, while the non dominant male spiders have a propensity to stay in the middle of the dominant male spider population. Then, the male spiders' position change depends on their weights and can be modeled as follows:

$$m_i^{(t+1)} = \begin{cases} m_i^t + \alpha v_i f_j (s_f - mi^t)\varphi(rand - \frac{1}{2}) \\ if w_j > w_{nm} \\ m_i^t + \alpha(\frac{\sum_{l=1}^m m_l^t w_l}{\sum_{l=1}^m w_l} - m_i^t) \\ if w_j < w_{nm} \end{cases} \tag{4.9}$$

Where: S_f is the position of the closest female to the spider i, wnm is the weight of the median spider and $(\frac{\sum_{l=1}^m m_l^t w_l}{\sum_{l=1}^m w_l})$ is the weighted mean position of male spider in the population.

6. Update the spider population members according to the mutation operator by adopting the roulette wheel technique.
   Mating takes place between dominant male spiders and female spiders within a specific range (range of mating) which can be computed using the following equation:

$$r = \frac{\sum_{j=1}^n (p_j^{max} - p_j^{min})}{2.n} \tag{4.10}$$

   Where p_j^{max} and p_j^{min} are respectively the maximum and minimum boundaries of the search space, whereas n is the dimension of the search

space.
The new spider (S_{new}) generated from the mating process is compared to the worst spider S_{worst} of the population in regards of its weight. If the new spider is better than the worst spider, this later is replaced by the new one. Otherwise, the colony does not change. In case of replacement, the new spider takes the same gender of the replaced spider.

7. Repeat the steps 2 to 7 until reach a termination criterion.

4.2.2 CLA -SSO Details

The objective of localization process by CLA -SSO approach is to estimate the locations of N unknown sensor nodes which are deployed randomly in the 2-dimensional (2D) space using prior information about the position of M anchor sensor nodes. The transmission range of both unknown sensor nodes and anchor nodes is R.
Our approach, first estimates the unknown sensor nodes locations by using the traditional Centroid Localization Algorithm. Second, it uses The SSO meta-heuristic to optimize the locations calculated by the CLA.

The main steps followed by our proposed algorithm to obtain optimal locations are given in the following subsections.

4.2.2.1 Initial Positions Estimation by CLA

In our algorithm, the first step of CLA is to estimate distances between every unknown node and anchor nodes within its transmission range. It is important to note that we take into account an additive noise when calculating estimated distances [11, 7]. Then the distance between an unknown node and each anchor node is calculated as follows: $d_a = d_a + n_a$, where d_a is the actual distance which can be calculated according to the following equation and n_a is a Gaussian noise .

$$d_a = \sqrt{(x - x_a)^2 + (y - y_a)^2} \tag{4.11}$$

Where (x, y) are the coordinates of the unknown sensor node and (x_a, y_a) are the coordinates of the anchor sensor node.
Once estimated distances are calculated, each unknown node checks if there are at least three anchor sensor nodes within its transmission range, if it is the case, that sensor node is considered as localizable node and it can estimate its location by using the equation (2.1). we note that each unknown sensor node uses the three nearest anchor node ($k = 3$) to estimate its position by CLA.
Nodes succeed to obtain their locations by CLA (nodes have at least three anchor sensor nodes in their transmission radius) are optimized by the SSO as in the following subsection.

4.2.2.2 Locations Optimization by SSO

At the beginning of the optimization process, our algorithm generates randomly N_s spiders (N_f female spiders and N_m male spiders) around each position initially calculated by traditional CLA. Then, each unknown sensor node runs the SSO meta-heuristic to find out its optimal location. Our proposed method minimizes in each iteration the objective function described in the following equation:

$$f(x, y) = \frac{1}{m}(\sum_{a=1}^{k} \sqrt{(x - x_a)^2 + (y - y_a)^2} - d_a)^2 \tag{4.12}$$

Where (x, y) the estimated coordinates of the unknown node, (x_i, y_i) the coordinates of the anchor nodes $a = 1, \ldots .k$, d_i the estimated distance between anchor nodes, the unknown node and m the number of neighboring anchor nodes to this unknown node.

At the end of each generation of the SSO method, the estimated position of each sensor node is compared to the position obtained in the previous iteration in terms of its fitness. The best location (location which has the min distance to the neighboring anchor nodes) becomes the optimal position of the target sensor node.
Finally, after a maximum number of iterations ($MaxIter$), CLA-SSO finds out the optimal positions of unknown nodes.

The main steps of the proposed algorithm CLA-SSO are described below:
Step1: Deploy Randomly N unknown nodes and M anchor nodes in $2-D$ space.
Step2:

- Calculate distances between unknown sensor nodes and anchor nodes to determine the set of localizable nodes (nodes haves at least 3 neighboring anchor nodes) $UL = (UL_1, UL_2...UL_n)$.
- Determine R, $maxIter$ and N_s.

Step3: Find out initial positions by CLA.
Step4:

- Define the initial set of optimal positions as the set of initial position find by CLA.
- Generate N_s spiders (N_f female and N_m male spiders) around each initial position.

Step5: Calculate the fitness value of each spider.
Step6: Update the set of optimal positions.
Step7: Calculate weighs.
Step8: Calculate vibrations received by each spider.
Step9: Update spiders' positions based on their gender.
Step10: Update the spider population by applying mutation operator.

Step11: Repeat the steps from 5 to 11 until reach the maximum number of iterations.

4.3 Node Localization Optimization in WSNs by Using Cat Swarm Optimization Metaheuristic

4.3.1 Cat Swarm Optimization Algorithm

Cat Swarm Optimization Algorithm is a metaheuristic inspired from the resting and tracing behaviors of cats [88, 89]. To resolve an optimization problem, the CSO algorithm uses N cats where each cat represents a possible solution for the problem. A set of cats is divided into two groups depending on a mixture ratio which defines the number of cats in each group. To mimic the real behavior of cats the number of cats in the first group where cats move according to the seeking mode is more than of those in the second which move according to the tracing mode.
The original CSO algorithm follows many steps to resolve an optimization problem as described below [15]:
Step1: Generate the initial population by creating N cats.
Step2: Divide the cats' population into seeking and tracing mode by defining a flag.
Step3: Evaluate the fitness value of each cat and save the cat which has the best fitness.
Step4: Update cats positions depending on their group (seeking or tracing mode).
Step5: Assign each cat to seeking or tracing mode.
Step6: Repeat the steps from 3 to 6 until reach the termination criteria.
In order to enhance the performances of CSO algorithm, many variantes are

proposed such in [90, 91, 92, 93, 94]

4.3.1.1 Seeking Mode

In this mode, four parameters are defined: Seeking Memory Pool **(SMP)** which represents the size of seeking memory for each cat. The number of copies created for each cat, where one of these copies will be selected as the best solution of the cat., Seeking Range of the selected Dimension **(SRD)** which is used to ensure that the modified dimensions stay in the range of the valid values, Counts of Dimension to Change **(CDC)** which defines the number of dimensions to be modified and Self-Position Considering **(SPC)** which specifies whether the current cat's position can be candidate for the next movement or not.
The main steps of the seeking mode are as follows[1]:
Step1: Create C copies of the current cat where: $C = SMPifSPC = TrueelseC = SMP - 1otherwise$ (in this case the current cat is considered as possible next position of the current cat)
Step2: For each copie, based on the CDC value update the position of the current copie of the cat as follows:

$$pjd_{new} = (1 \pm (r * SRD)) * pjd_{old} \tag{4.13}$$

where pjd_{old} is the current position of the copie j; pjd_{new} is the next position; j is the number of the copie of a cat (j=1:C) and d is the dimension; and r is a random number within the range [0, 1].
Step3: Calculate the objective function (Fitness) of all copies of cat
Step4: Select the copie of cat to be a next position of the current cat based on the probability defined in the following equation:

$$P_j = (\frac{|(Fitness_j - Fitness_b)|}{Fitness_{max} - Fitness_{min}}) \tag{4.14}$$

Where $Fitness_b = Fitness_{max}$ if the problem is a minimization problem, otherwise $Fitness_b = Fitness_{min}$.

4.3.2 Tracing Mode

In this mode, the cat's movement is based on the velocity of each dimension which is defined randomly in the first iteration. The main steps of this mode are described as follows:

Step1: Calculate the objective function (Fitness) of all cats

Step2: Update the velocity of each dimension based on the following equation:

$$V_{k,d} = V_{k,d} + rand * c(X_{best,d} - X_{k,d}) \tag{4.15}$$

Where $X_{best,d}$ is the position of the dimension d of the curent copie of the cat with the best fitness, $X_{k,d}$ is its current position.

Step3: Verify the velocity values of each cat and define the velocities which are higher than the maximum velocity to be equel to a limit.

Step4: Update the position of cat using the following equation:

$$X_{k,d} = X_{k,d} + V_{k,d} \tag{4.16}$$

4.3.3 CLA-CSO for Node Localization Optimization

The localization algorithm proposed in this paper works in two phases. The first phase is similar to the first phase of the CLA-SSO algorithm where the unknown sensor nodes locations are estimated by using the traditional Centroid Localization Algorithm. These locations are optimized by the CSO metaheuristic in the the second phase.

The main steps followed by our proposed algorithm CLA-CSO to calculate optimal locations are given in the following subsections.

4.3.3.1 Locations Optimization by CSO

In this phase, nodes localized by CLA (nodes have at least three anchor sensor nodes in their transmission radius) in the first phase are optimized by the CSO.
The optimization process in CLA-CSO algorithm is as follows: to initialize the initial population, N cats are generated randomly around each position estimated by traditional CLA in the first phase. These cats are considered as a possible position of the unknown sensor node. After, every unknown sensor node runs the CSO meta-heuristic to estimate its optimal location. Our proposed algorithm is an iterative algorithm which minimizes the objective function described in equation 4.12:

After every iteration, the CSO compare the current cat to the cat of the precedent iteration in terms of the fitness value and keep in memory the best one (this cat becomes the optimal position of the unknown sensor node).

The main steps followed by CLA-CSO for node localization optimization are as follows:
Step1: Deploy Randomly N unknown nodes and M anchor nodes in search space.
Step2:

- Calculate distances between unknown sensor nodes and anchor nodes to determine the set of localizable nodes (nodes haves at least 3 neighboring anchor nodes) $UL = (UL_1, UL_2...UL_n)$.
- Determine R, $maxIter$ and N_c.

Step3: Estimate initial positions by CLA.
Step4: Generate N_c cats around each initial position.
Step5: Divide the N_c cats of each node to move into seeking or tracing mode.
Step6: Move each cat according to its groupe (seeking mode or tracing

mode).
Step7: Calculate the fitness value of each cat.
Step8: Update the set of optimal positions.
Step9: Redistribute the cats into seeking or tracing mode according to a mixture ratio.
Step10: Repeat the steps from 6 to 10 until reach the maximum number of iterations.

4.4 Simulation Results

In order to evaluate the performance of our proposed algorithms namely CLA-SSO and CLA-CSO, simulations are done by using the MATLAB platform. Then, the proposed algorithms are compared to the original CLA in terms of localization error and average localization error.

In our simulation, we use a square area of 50*50 m^2, and both of unknown sensor nodes and anchor sensor nodes are deployed randomly and have a transmission radius set to $20m$.

For the CLA-SSO algorithm parameters, we deploy ten (10) spiders around each position found by the CLA, so the size of the spider colony is $NL * 10$, where NL is the number of the sensor nodes localized by CLA.
Among the ten spiders deployed around every location, we use seven (7) female spiders and three (3) male spiders. So, the total number of female spiders in the population is calculated as a multiplication of the total number of nodes localized by CLA and 7 according to the following equation:

$$Nf = NL * 7 \tag{4.17}$$

And the total number of male spiders in the population is calculated by multiplying the total number of nodes localized by CLA and 3 as shown in the equation:

$$Nm = NL * 3 \tag{4.18}$$

The parameters of CLA-CSO are as follows: we deploy ten (10) cats around each position found by the CLA, a mixture ration is defined as 0.03, so the seeking population represent 70% of the whole population of cats.

In order to evaluate the performance of the proposed algorithms, 50 unknown sensor nodes and 10 anchor nodes are deployed randomly in the simulation environment, then the localization error of each localized sensor node and the average localization error are calculated according to the following two equations: equation (4.19) and the equation (4.20) respectively.

$$error_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{4.19}$$

This error represents the distance between the estimated location (x, y) and the reel location (x_i, y_i) of each localized sensor node.

$$Averageerror = \frac{1}{NL} \sum_{i=1}^{NL} \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{4.20}$$

Where (x, y), (x_i, y_i) are the reel and the estimated coordinates of the unknown node respectively and NL is the number of localized nodes in the network (nodes can be localized by CLA).

Figure 4.1 represents the localization error of every unknown sensor node for both basic CLA and CLA-SSO algorithm, Results obtained show clearly that CLA-SSO algorithm reduces the localization error of the original CLA which reduce also the average of localization error from 5.64123 in basic CLA to 3.25691 in CLA-SSO as shown in the Table 4.1.

Table 4.1: Average localization error for CLA and CLA-SSO algorithms

	CLA	**CLA-SSO**
Average localization error	5.64123	3.25691

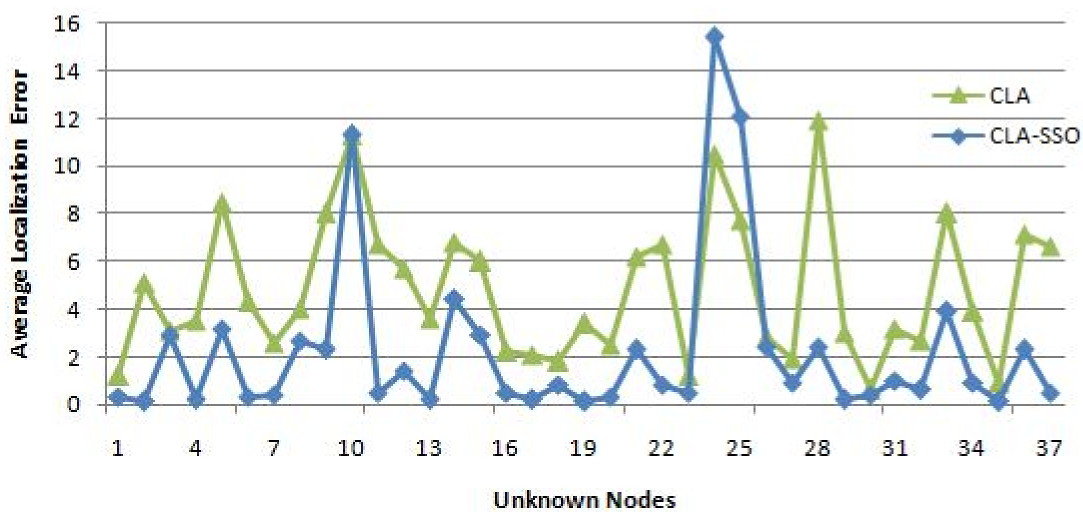

Figure 4.1: Localization error for every unknown node for both CLA and CLA-SSO algorithms

Fig. 4.2 represents the localization error of each unknown sensor node for both basic CLA and CLA-CSO algorithm. Results show clearly that our proposed algorithm reduces the localization error of the original CLA which reduce also the average of localization error from 5.64123 in basic CLA to 0,66249 in CLA-CSO as shown in the Table 4.2.

Table 4.2: Average localization error for CLA and CLA-CSO algorithms

	CLA	**CLA-CSO**
Average localization error	5.64123	0,66249

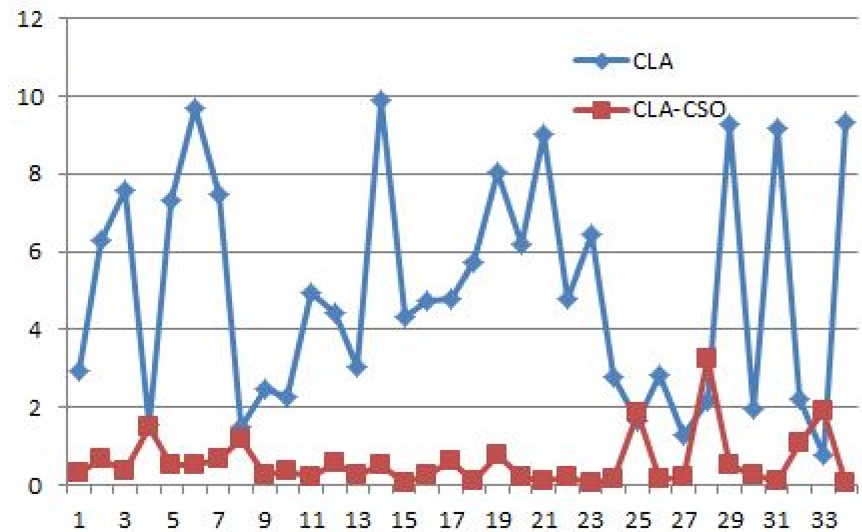

Figure 4.2: Localization error for every unknown node for both CLA and CLA-CSO algorithms

In order to show the results of localization by both algorithms CLA-SSO and CLA-CSO in different configuration, the average localization error is calculated by changing some parameters, first we fix the number of unknown nodes and the transmission range and change the values of the ratio of anchor nodes. Second, we change the number of unknown nodes and fix the other parameters. Finally, we change the communication range and we fix the other parameters.

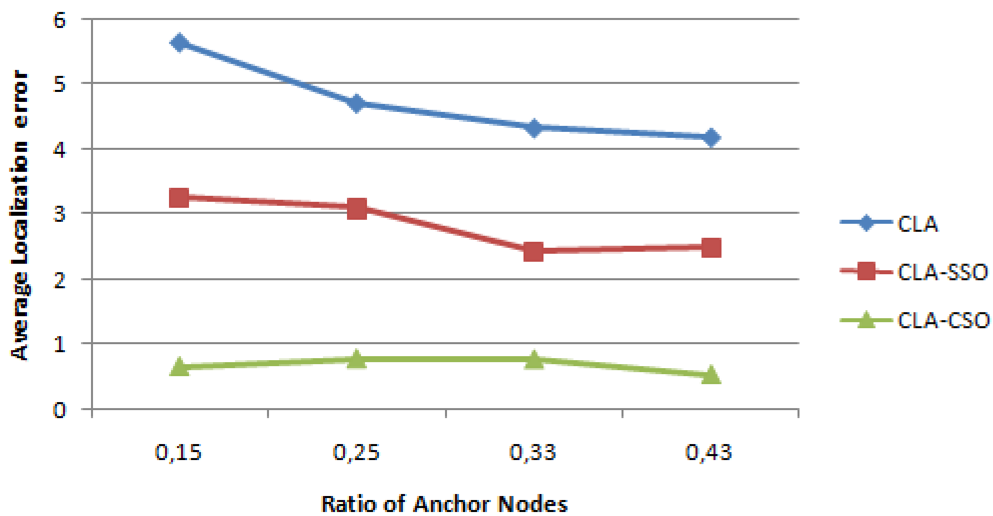

Figure 4.3: Caption: Average localization error Vs Ratio of anchor nodes simulation results

Simulation results shown in Figure 4.3 represent the average localization error of three algorithms, CLA CLA-SSO and CLA-CSO by variating the ratio of anchor nodes and fixing the other parameters. These results show that the average localization error is reduced in both CLA-SSO and CLA-CSO in comparison to the traditional CLA which prove the effectiveness of metaheuristic algorithms in optimizing the localization of traditional localization algorithms. We can see also that the average localization error is reduced significantly in CLA-CSO compared with CLA-SSO which prove that CSO metaheuristic is more effective than SSO metaheuristic in localization optimization. In addition,simulation results show that the average localization error decreases when ratio of the anchor nodes increases and thus for the three algorithms CLA, CLA-SSO and CLA-CSO.

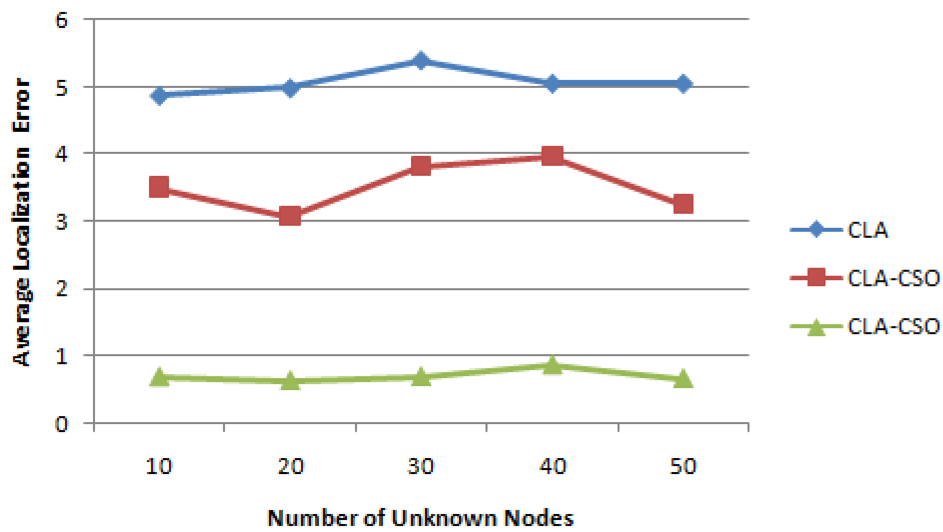

Figure 4.4: Average localization error Vs number of unknown nodes simulation results

Average localization error of the algorithms CLA, CLA-SSO and CLA-CSO calculated by changing the number of unknown nodes from 10 to 50 is shown in Figure 4.4. Results show that the average localization error stay stable for different number of unknown nodes. In addition, the average localization error is minimized in CLA-CSO compared to traditional CLA and CLA-SSO .From thesse results, we can conclude that CLA-CSO algorithm outperforms both CLA and CLA-SSO.

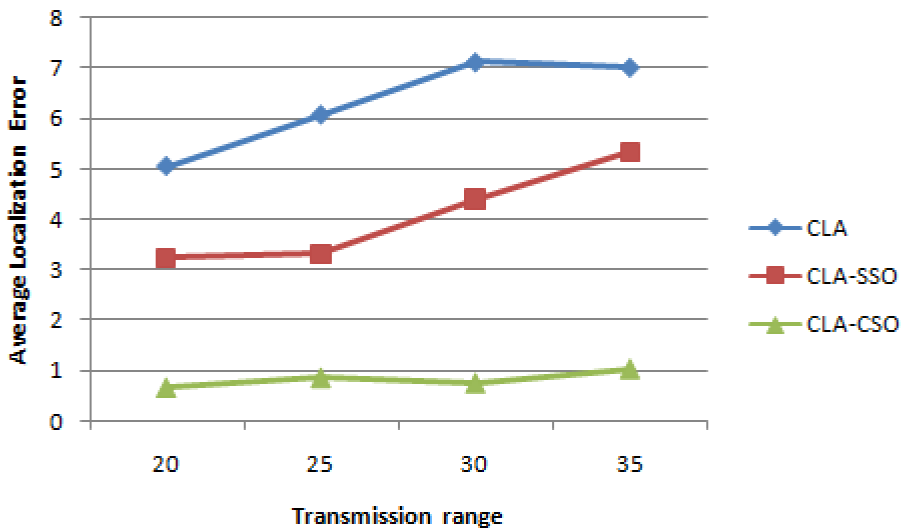

Figure 4.5: Average localization error Vs communication range simulation results

Figure 4.5 illustrate the simulation results obtained by variegating the communication range and calculating the average localization error of three algorithms, basic CLA, CLA-SSO and CLA-CSO algorithms. From this figure, the average localization error is increased when increasing the communication range, and it is minimized in CLA-CSO compared to basic CLA and CLA-SSO algorithms.

4.5 Conclusion

The main objective of the proposed algorithms in this thesis is to increase the localization accuracy by decreasing the localization error. To reach our aim, we used the SSO and CSO metaheuristics to optimize the localization of the traditional CLA. In our proposed algorithms, the locations firstly obtained by the CLA are optimized by using either SSO or CSO meta-heuristic algorithms. Simulation results showed that our proposed methods reduce significantly the localization error compared to the basic CLA. Then we can conclude that the meta-heuristic optimization algorithms are suitable techniques to improve the localization accuracy of the traditional localization algorithms. In addition, the CLA-CSO algorithm outperform both traditional CLA and CLA-SSO which prove that CSO metaheuristic is more effective in optimizing the localization in WSNs in comparison to the SSO metaheuristic.

CONCLUSION

Wireless sensor networks have become widely used in various applications in different fields. However, To ensure their effectiveness many issues must be resolved. Localization is one of the most challenges in Wireless Sensor Networks (WSNs)as many WSN applications depend on the positions information of the randomly deployed sensor nodes. Many localization algorithms have been proposed. These algorithms can be classified into range based and range free. These later are more efficient but its main weakness is the presence of error in positions calculation which does not meet the need of some applications to know the most possible accurate positions of sensor nodes. Limitations of traditional localization algorithms in terms of precision led to thinking about using optimization techniques to enhance the localization performances. Several techniques have been used for localization optimization.

The aim from this thesis is the study of localization schemes, the optimization of the localization in WSNs by adopting metaheuristic optimization algorithms and the development of new localization optimization algorithms using metaheuristic able to enhance the localization accuracy of traditional localization algorithms. Before this, the luck of classification of the optimization techniques used in WSNs localization has motivated us to propose a new one in this thesis. We classified localization optimization techniques as machine learning based localization optimization techniques, mobile anchor node based localization optimization techniques, mathematical model for localization optimization and metaheuristic based localization optimization techniques.

Metaheuristic optimization algorithms have shown their effectiveness in solving optimization problems and in improving localization accuracy with a minimum of execution time and computational complexity.

In the other hand, centroid localization algorithm is one of the most range free used algorithms due to its simplicity, feasibility and less hardware cost, but it shows poor localization accuracy and need to be enhanced by optimizing the localization error. For this target, metaheuristic optimization algorithms are adopted. Two new schemes were proposed in this thesis to improve the localization accuracy of traditional CLA and find out the most possible optimal unknown sensor nodes positions. The first scheme called (CLA-SSO) is an hybridization between the CLA and the SSO metaheuristic, whereas, The second scheme namely (CLA-CSO) is a combination between CSO metaheuristic and traditional CLA.

In this thesis, the new proposed taxonomy of localization optimization techniques in WSNs was explained and the CLA-SSO and CLA-CSO algorithms were well described. Furthermore, the proposed schemes were simulated by using the Matlab platform. Simulation results are obtained by changing some parameters including the ratio of anchor nodes, the number of unknown nodes and the transmission radius and the average localization errors were analyzed to prove the efficiency of the proposed algorithms. Finally, comparison of the proposed approaches with each other and with the

CLA was provided.

The use of metaheuristic algorithms has proved its efficiency in improving the accuracy of the CLA, and this is shown by the significant reduction of the localization error. Furthermore, the CLA-CSO algorithm has given good results compared with the CLA and the CLA-SSO in terms of localization accuracy. From this, we can conclude that the metaheuristic are suitable algorithms for localization optimization, but the efficiency of the algorithm depends on the choice of the metaheuristic because each metaheuristic can provide different results with the same configuration and traditional algorithm.

Localization in WSNS is an important research field, localization algorithms can be enhanced and new one can be developed, but the choice of the best localization algorithm remains a challenge. As an interesting future research direction, we would like to provide a study about the selection of the best localization algorithm as well as the choice of the best metaheuristic for localization optimization. In addition, we would like to test our proposed algorithms for localization optimization in 3D environment.

CONTRIBUTIONS

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Resumé

Les réseaux de capteurs sans fil ont été utilisée dans diverses applications. La plupart de ces applications utilisent un déploiement aléatoire d'un nombre important de nœuds capteurs dû soit à l'hostilité de la zone à surveiller, soit à son immensité. L'étape de localisation est donc nécessaire non seulement au fonctionnement du réseau, mais aussi à l'exploitation des données collectées. Il faut donc localiser avec la meilleure précision possible tous les nœuds du réseau. Plusieurs algorithmes ont été proposés dans la littérature pour résoudre le problème de localisation, cependant, ces algorithmes souffre de la présence d'erreur dans les positions estimées. Ainsi, ils doivent être ameliorées. L'objectif de cette thèse est de développer de nouveaux algorithmes de localisation utilisant des métaheuristiques dans le but de réduire l'erreur de localisation et d'améliorer la précision. Pour atteindre notre objectif, nous avons proposé deux nouveaux algorithmes de localisation. Le premier algorithme est basé sur l'algorithme de localisation Centroid et la métaheuristique d'optimisation de l'araignée sociale (CLA-SSO) et le second algorithme est basé sur l'algorithme de localisation Centroid et la métaheuristique d'optimisation de l'essaim de chat. Afin de montrer les performances des algorithmes proposés, ils sont simulés et comparés avec l'algorithme de localisation Centroid.

Mots clés:
Réseaux de capteurs sans fil, Localisation, Optimisation, Metaheuristiques, SSO, CSO.

Abstract

Wireless Sensor Networks (WSNs) technology has been used in various applications. Most of these applications use a random deployment of an important number of sensor nodes due either to the hostility of the area to be monitored, or to its vastness. The localization process is therefore necessary not only for the functionning of the network, but also for the exploitation of the collected data. It is therefore necessary to locate with the best possible precision all the nodes of the network. Several algorithms have been proposed in the literature to overcome the localization problem, however,the main weakness of these algorithms is the presence of error in the estimated locations. Thus, they need to be enhanced. The objective of this thesis is to develope new localization algorithms using metaheuristic with the aim to reduce the localization error and enhance the accuracy. To acheive our aim we proposed two new localization algorithms. The first algorithm based on Centroid Localisation Algorithm and Social Spider Optimization metaheuristic (CLA-SSO)and the second algorithm based on Centroid Localization Algorithm and Cat Swarm Optimization metaheuristic. In order to show the performance of the proposed algorithms, they are simulated and compared with the localization algorithm CLA.

Keywords:
Wireless Sensor Networks, Localization, Localization Optimization, Metaheuristic, SSO, CSO.

ملخــص

تم استخدام شبكات الاستشعار اللاسلكية في تطبيقات مختلفة مثل مراقبة البيئة، التطبيقات العسكرية، تطبيقات الرعاية الصحية، إدارة الكوارث وغيرها. تستخدم معظم هذه التطبيقات نشرًا عشوائيًا لعدد كبير من عقد الاستشعار إما بسبب عدائية المنطقة المراد مراقبتها أو اتساعها. لذلك فإن خطوة تحديد الموقع ضرورية ليس فقط لتشغيل الشبكة و لكن أيضًا لاستغلال البيانات التي تم جمعها. لذلك، من الضروري تحديد موقع جميع عقد الشبكة بأكبر قدر ممكن من الدقة. تم اقتراح العديد من الخوارزميات لحل مشكلة التوطين، إلا أن هذه الخوارزميات تعاني من وجود خطأ في المواضع المقدرة مما يستدعي ضرورة تحسينها. الهدف من هذه الرسالة هو تطوير خوارزميات توطين جديدة باستخدام خوارزميات الخصائص الوصفية لتقليل خطأ التوطين وتحسين الدقة. لتحقيق هدفنا، اقترحنا خوارزميتين جديدتين للتوطين. تعتمد الخوارزمية الأولى على خوارزمية موقع المركز و خوارزمية القطط، أما الثانية فهي تعتمد على خوارزمية موقع المركز و خوارزمية العنكبوت الاجتماعي. من أجل إظهار أداء الخوارزميات المقترحة و فعاليتها، تمت محاكاتها ومقارنتها fخوارزمية موقع المركز.

كلمات مفتاحية:
شبكات الاستشعار اللاسلكية، التوطين، تحسين التوطين، خوارزميات الخصائص الوصفية، خوارزمية القطط، خوارزمية العنكبوت الاجتماعي