DEVELOPMENT OF AN ARTIFICIAL FISH SWARM ALGORITHM BASED ENERGY EFFICIENT TARGET TRACKING SCHEME IN WIRELESS SENSOR NETWORKS

BY

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DECLARATION

I LAWAL Samira Abdulhamid hereby declare that this dissertationtitled**"DevelopmentofanArtificialFishSwarmAlgorithmBasedEnergyEfficientTarget Tracking Schemein Wireless Sensor Networks"** wascarriedoutbyme in the Department of Electrical and Computer Engineering. The information derived from literature has been duly acknowledged in the text and a list of references provided. To the best of my knowledge, no part of this dissertation was previously presented for another degree or diploma at this or any other institution.

Samira Abdulhamid LAWAL ______________________ ________________
(Student)

CERTIFICATION

This dissertation titled "DEVELOPMENT OF AN ARTIFICIAL FISH SWARM ALGORITHM BASED ENERGY EFFICIENT TARGET TRACKING SCHEME IN WIRELESS SENSOR NETWORKS" by Samira Abdulhamid LAWAL meets the requirements for the award of degree of Master of Science (MSc) in Telecommunication engineering by Ahmadu Bello University, Zaria and it is approved for its contribution to knowledge and literary presentation.

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DEDICATION

This research work is dedicated to my children; Zafirah, Zakiyah and Zayd.

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In the name of Allah (SWT), the most gracious, the most merciful. All praisesare to the One to Whom all Dignity, Honor and Glory are due; the Unique with perfect attributes, Who begets not, nor is He begotten. He has no equal but he is the Almighty, Omnipotent. Peace and Blessings of Allah be upon all the Prophets and Messengers, particularly on Muhammad (SAW), the last of the Prophets, and on all who follow him in righteousness until the Day of Recompense.

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ABSTRACT

Optimal deployment of sensor node in other to ensure optimum network coverage is one of the challenging problems faced by Wireless Sensor Network (WSN) researchers due to the complexity and exhaustive nature of WSN. Target tracking problem is concerned with maximizing the lifetime of the network while continuously monitoring a set of targets.This dissertation presents an optimal deployment of WSN and target tracking scheme using the intelligent swarming behaviours of Artificial Fish Swarm Algorithm (AFSA). The preying, swarming and chasing behaviours of AFSA were initially replicated using MATLAB R2013b simulation environment. The position of network nodes were randomly deployed in a network coverage area of 60 square meters with a total of 60 sensor nodes of 4m radius and communication range of 15m using the replicated AFSA algorithm. Thereafter, the replicated AFSA was used to detect event based on target discovery probability model. A series of simulation were performed, and results showed that the proposed technique can attain maximum network coverage of 77.87% when the number of iteration was 25 after which it kept an almost constant value for the rest of the simulation process. The relationship between network coverage and number of mobile nodes also showed that network coverage increased with increase in mobile nodes. The approach indicated maximum network coverage of 80.07% when the mobile node was 50. Thereafter, it tended towards stability when the number of network nodes was above 50. Effects of various attenuation factors on the proposed model were evaluated and simulation results shows that the proposed method successfully attains maximum network coverage of 70.58%, 70.99%, 72.69% and 77.15% when the attenuation factors are 0.75, 0.8, 0.85 and 0.90 respectively. Target tracking simulation scenarios were presented and results showed that the computation energy required to successfully track 30, 45 and 60 targets were 21.63%, 28.003% and 36.99% less than the energy (time taking) required to track the 15 targets respectively.

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LIST OF ABBREVIATIONS

ABC	Artificial Bee Colony
AF	Artificial Fish
AFSA	Artificial Fish Swarm Algorithm
CKF	Centralized Kalman Filter
DKF_DC	Distributed Kalman Filtering Approach with Dynamic Clustering
DKF_GOSSIP	Distributed Kalman Filter with Gossip Communications
DKF_LSR	Distributed Kalman Filter with Limited Sensing Range
DOT	Dynamic Object Tracking
FIS	Fuzzy- Logic Inference System
GPS	Global Positioning System
HCTT	Hybrid Cluster-Based Target Tracking
IMM	Interactive Multiple Model
LPC	Linear Prediction Coefficients
MCTA	Minimal Contour Tracking Algorithm
MCH	Master Cluster Head
NCA	Network Coverage Area
NCV	Nearly Constant Velocity
PSO	Particle Swarm Optimization
RMSE	Root Mean Square Error
SF	Schedule Flooding
SU	Schedule Updating
SN	Sensor Nodes
SOA	Self Organization Algorithm

SCH	Slave Cluster Head
SSMTT	Sleep Scheduling in Sensor Networks for Multiple Target Tracking
TDSS	Target Direction-Based Sleep Scheduling
TF	Threshold Flooding
TOSSIM	Tiny Operating System for Wireless Sensor Motes
WSN	Wireless Sensor Network
WSNs	Wireless Sensor Networks

CHAPTER ONE

INTRODUCTION

1.1 Background

Wireless Sensor Networks (WSNs) are increasingly being used for collecting data, such as physical and environmental properties, from a geographical region of interest due to advancements in electronics and wireless communication technology. WSNs are composed of a large number of tiny, low-power, low-cost sensor nodes which have the ability to sense physical phenomena, process data, and communicate with one another (Alikhani, 2010). A sensor node is a tiny device that includes four basic components: a sensing subsystem for data acquisition from the physical surrounding environment, a processing subsystem for local data processing and storage, a wireless communication subsystem for data transmission and a power supply subsystem, which are batteries. A large number of these wireless sensor nodes are deployed across a geographical region to form a WSN. These WSNs create smart environments by providing access to information regarding the environment through collecting, processing, analyzing, and disseminating data whenever required (Alikhani, 2010). In order to use WSNs in inaccessible terrains or disaster relief operations, random deployment of the sensor nodes is required. As a result, the position of these nodes will not be predetermined and thus the nodes must have the ability to collaborate with each other to form self-organized networks in order to perform tasks including but not limited to determining their location (Akyildiz*et al.*, 2002).

WSNs have numerous applications, which include environmental monitoring, specifically for planetary exploration, geophysical monitoring, habitat monitoring, oceanography, wildlife tracking and target tracking. Target tracking is useful in keeping check on movements of individuals (pedestrians or mobile), in congested areas; such as business district of cities, government buildings, nuclear facilities, borders, seaports, airports and national monuments. Another promising application of WSNs is in the field of physiological monitoring and medical sensing (Alikhani, 2010). WSNs can also be used in smart homes and offices where they can efficiently regulate light, temperature, and humidity based on predefined individual preferences. Other uses of WSNs are in inventory tracking, precision agriculture, disaster detection, search and rescue operations, and commercial and residential security. In a military context, WSNs can be used for surveillance and battle-space monitoring. WSNs can also be used in transportation such that vehicles equipped with wireless sensors form local communication networks. These networks allow the vehicles to share information on weather and road conditions, plan routes, avoid traffic, and identify their position in areas where Global Positioning System (GPS) signals are unavailable (Alikhani, 2010).

A sensor network deployment can be categorized as either a dense deployment or a sparse deployment. A dense deployment has a high number of sensor nodes in the given field of interest while a sparse deployment has fewer nodes. The dense deployment model is used in situations where it is very important for every event to be detected or when it is important to have multiple sensors cover an area. Sparse deployments may be used when the cost of the sensors makes a dense deployment prohibitive or when there is the need to achieve maximum coverage using the barest minimum number of sensors (Mulligan, 2010). Malik (2005) stated that sensors can be deployed in any facility or area which has to be sensed in three main ways:

1) Triangular sensor deployment: Sensors are placed in a triangular fashion.

2) Square sensor deployment: Sensors are arranged in square position.

3) Irregular sensor deployment: Sensors arrangement is uneven.

These deployments are depicted in Figure 1.1 (Malik, 2005).

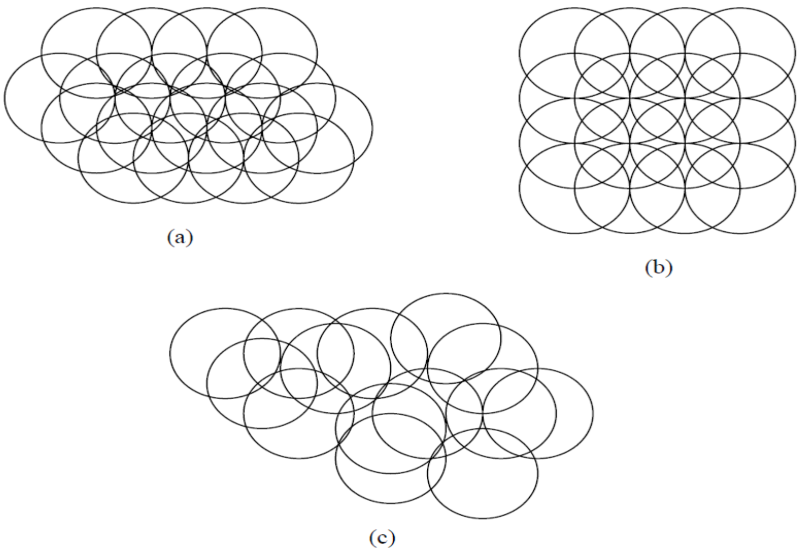


Figure1.1.WSN Deployments: ((a) Triangular (b) Square and (c) Irregular) (Malik, 2005).

The following are factors to consider in Wireless Sensor Network Deployment:

a) Scalability: A sensor network typically comprises of a large number of nodes spread randomly throughout the area. Scalability includes reliability of command dissemination and data transfer, management of large volume of data and scalable algorithms for analysing the data. Therefore, managing all these becomes a very difficult task. However, the number of nodes depends on the application. Distributed and localized (such as: Trilateration and Swarm) algorithmsare essential in these cases. In WSNs, increasing the number of sensors in an area does not lead to better tracking results; since beyond a critical threshold (0.9) increasing the number of sensors does not improve the location precision in tracking. Hence, the placement of the sensors in an area should be so as to maintain a balance between number of sensors and coverage required (Tseng *et al.*, 2003).

b) Stability: Since sensors are likely to be installed in outdoor or even hostile environments, their failure is an issue of concern always. The system must be able to operate well without supervision. This unattended mode of operation is common nowadays (Malik, 2005).

c) Power: Sensors are deployed in different terrains and since no source of power supply is available, sensor devices are operated by battery. Hence, energy conservation is a prime concern at all times. Operations such as on-board signal processing and communication with neighbouring nodes consume a lot of energy. Thus, energy awareness has to be incorporated in every aspect of design and operation which means it is an integral part of groups of communicating sensor nodes and the entire network and not only in the individual nodes (Malik, 2005).

Target tracking is the application of WSN whose goal is to trace the roaming path of an object which is considered as a target and to detect the position of target. As WSN continuously monitor the environment, it provides the space to enhance the energy efficiency. Target tracking scheme comprises of three interrelated subsystems which are shown in Figure 1.2.

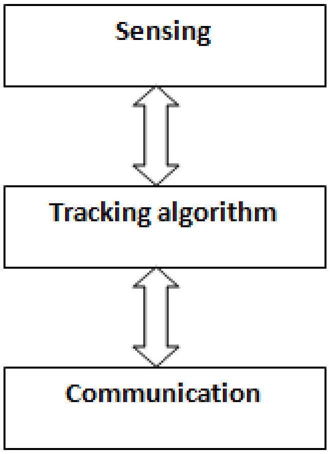


Figure1.2: Target Tracking Scheme Classification (Chauhan&Ahlawat, 2014) .

The sensing subsystem is used to sense the target i.e. it comprises of the node that first detects the target and other nodes which gradually take part in detecting the target. The second subsystem is the prediction based algorithm which is used to trace the path of the desired target. The third one is the communication subsystem which is used to send the information from one node to another. All these three subsystem work collaboratively and maintain the relationship among themselves(Chauhan&Ahlawat, 2014). This research, consist of two parts, the first part focuses on optimal deployment of sensor node using artificial fish swarm algorithm while the second part focused on target tracking taking into account energy management at node level.

1.2 Aim and Objectives

The aim of the research is the development of an Artificial Fish Swarm Algorithm (AFSA) based energy efficient target tracking scheme in Wireless Sensor Networks (WSN).

The objectives of the study are as follows:

1) Replication of the Preying, Swarming and Chasing behaviours of Artificial Fish Swarm Algorithm for optimal deployment of WSN.
2) Deployment of WSN nodes using the Replicated AFSA in (1) and the development of target tracking scheme using node tracking probability model.
3) Simulation and performance evaluation of the developed model in 2) using MATLAB R2013b Communication/Control toolboxes and validation by comparison with results obtained in Yiyue *et al.*, (2012)

1.3 Statement of Problem

Sensor node deployment is crucial to Wireless Sensor Network (WSN) energy efficiency. Inapt deployment cause inappropriate node concentration (high density). This creates message collisions and retransmissions, signal intrusions and cramming, huge energy consumptions, communication slit among others on the WSN. These in turn creates challenges on the scalability, stability, distributed architecture, energy consumption and autonomous operations of the WSN. The managing of the random spread of nodes in a coverage area is tasking due to dependence on applications (distributed and localized). The challenge is improving precision location-tracking problem, with emphasis on tracing the roaming path of node in a coverage in which sensors are deployed using AFSA.

1.4 Scope and Limitations

The limitations of this research work are highlighted as follows:

i. Time delay and synchronization.
ii. Optimization of power and memory space.
iii. Computational limitations.

1.5 Methodology

The step by step procedures adopted in this research, which include the development of the Artificial Fish Swarm Algorithm (AFSA) and their applications in the wireless sensor network are highlighted as follows:

i) Initialization of population of AFSA (The number of wireless sensor nodes) which is N numbers of Artificial Fish (AF) in D problem dimension space and all other parameters (Visual distance, Step size and Crowdedness).
ii) Replication of AFSA using the
    a. Preying
    b. Swarming
    c. Chasing

iii) Initialize the WSN network model and search (deploy) the nodes in its sensor area using the replicated AFSA behaviours in (ii)

iv) Determination of the node detected by all other nodes in the network based on node probability.

v) Determination of target tracking time in order to evaluate the energy efficiency of the proposed technique

vi) Evaluation of the performance of the proposed model based on network coverage.

vii) Validation using the work of Yiyue *et al.*, (2012).

1.6 Dissertation Organization

The general introduction has been presented in Chapter One. Detail review of related literatures and relevant fundamental concept about the Target Tracking Techniques and the Tracking Algorithm (Artificial Fish Swarm Algorithm) is carried out in Chapter Two. The methodology and relevant mathematical models describing the Wireless Sensor Network and Optimization using Artificial Fish Swarm Algorithm were presented in Chapter Three. The analysis, performance and discussion of the result were presented in Chapter Four. Conclusions and recommendations makes up Chapter Five.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter consists of the review of the fundamental concepts and the review of similar works which are relevant to the scope of this research.

2.2 Review of Fundamental Concepts

Various concepts fundamental to the research work which are, the target tracking techniques and the tracking algorithm (Artificial Fish Swarm Algorithm) are presented in this section.

2.2.1 Target tracking techniques

Tracking techniques are mainly classified based on (Fayyaz, 2011):

The tracking techniques in Wireless Sensor Networks are as depicted in Figure 2.1.

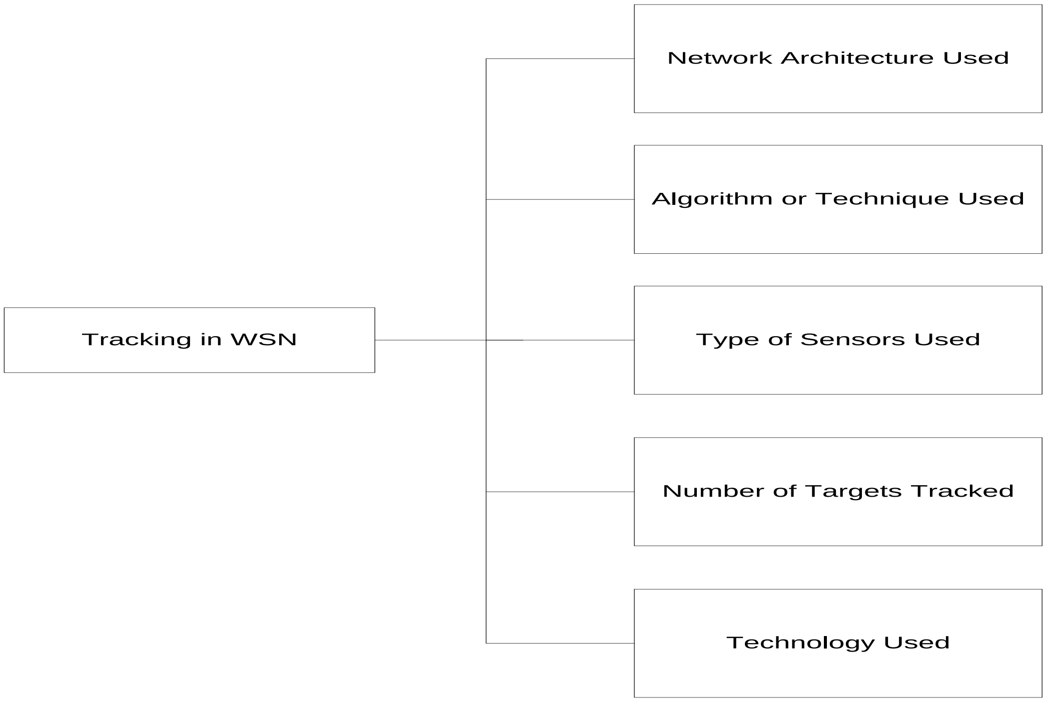


Figure 2.1. Basic Classification of Tracking Techniques in Wireless Sensor Networks (Fayyaz, 2011).

2.2.1.1 Network architecture

The following are the main types of network architectures that can be used for target tracking in sensor networks (Fayyaz,2011):

a) Cluster Based Architecture

b) Decentralized Architecture

c) Tree Based Architecture

An illustration of the classification of techniques based on network architecture used is shown in Figure 2.2.

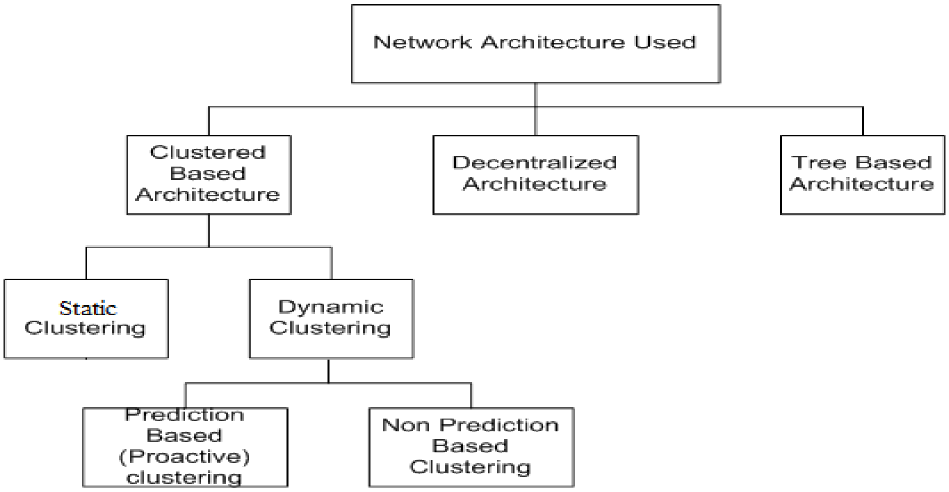


Figure 2.2. Classification of Techniques Based onNetwork Architecture (Fayyaz, 2011)

A. Cluster Based Architecture

In cluster based architecture there are several sensor nodes and for a certain group of nodes, they are assigned a cluster leader or cluster head. The cluster head is normally a high energy and high resource node. The introduction of cluster heads can reduce sufficient cost of network as one can deploy low cost low energy sensor nodes (Xu *et al.,* 2004). The cluster based architecture of wireless sensor networks can also be classified as:

i. Static Clustering

In static clustering the cluster heads are assigned to the respective sensor nodes at the time of formation of network and they cannot be changed. This means that throughout the working of wireless sensor network the nodes remain attach to the same cluster head as they were assigned (Yang &Sikdar, 2003).

ii. Dynamic Clustering

The dynamic clustering scheme can be of two types:

a) Prediction Based or Proactive Clustering

This scheme is mostly employed in a network of sleep sensors, where most of the sensors stay in the sleep mode. In prediction based clustering when a target moves from the region of one cluster head to the other, the current cluster head has to make an estimation or prediction about where the target is moving and correspondingly wakeup the next cluster head (Olule*et al.*, 2007).

b) Non Prediction Based Clustering

This scheme is used in a network of non-sleep sensors. Here the saving is not an issue instead the proper selection and the life time of cluster head is an issue. Based on the application environment a cluster head selection algorithm is run on each individual node, and the nodes collaboratively select the cluster head (Fayyaz, 2011).

B. Decentralized Architecture

In the decentralized architecture, there is no cluster head type of central entity in the network and in this case the network nodes are at the same level in terms of work responsibility. So the information regarding the target localization travels through the network to a central base station that is not the part of wireless sensor network. The base station can be a computer or some other computation entity. It runs an algorithm through which it can estimate the current location of the target (Aslam *et al.*, 2003).

C. Tree Based Architecture

In this case a tree structure is maintained across the network. The tree is rooted at the node that is closest to the target. Thus, as the target moves some nodes get added to the tree and some get deleted. This scheme reduces the overhead in terms of energy and information flow, as the information flows from the root to the end or periphery of the network through a particular route, as the information flows is controlled so energy consumption automatically gets controlled (Zhang & Cao, 2003).

In this research, the principle of cluster based network architecture is employed based on the intelligent swarming behaviours of school of fish. The behaviour of mobile network nodes moving towards larger network coverage is similar to the random, preying, swarming and chasing behaviours of fish. The food concentration of the artificial fish positions is regarded as the network coverage area of current location.

2.2.1.2 Tracking algorithm

According to the algorithm used, the tracking techniques can be classified as (Fayyaz, 2011);

1) The network of sleep sensors.

2) Target reporting.

3) Target chasing.

For the network of sleep sensors there is a further classification based on whether prediction heuristics are used or sensor scheduling is used.The classification of techniques based on tracking algorithm is shown in Figure 2.3.

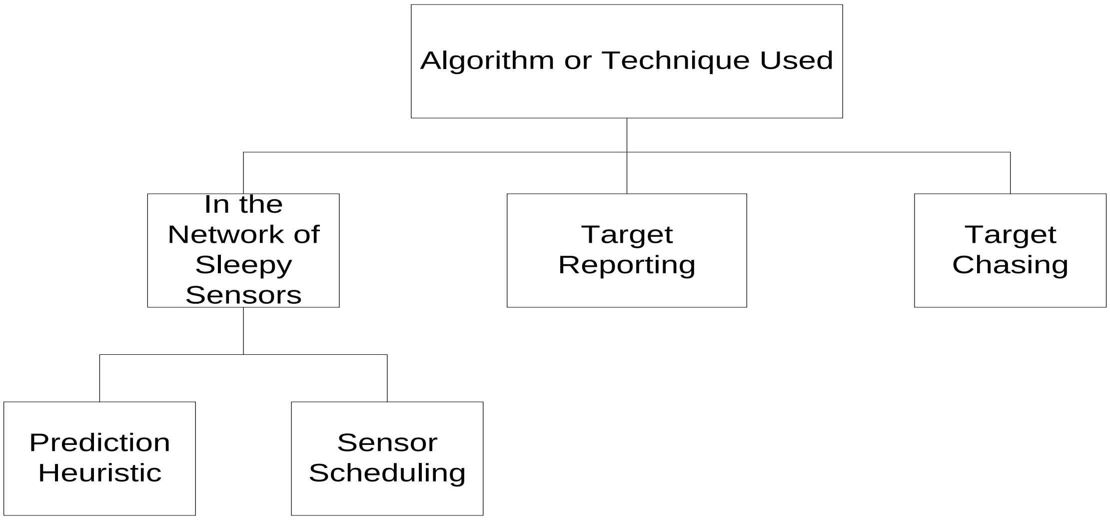


Figure 2.3.Classification of Techniques Based onAlgorithm or Technique (Fayyaz, 2011).

1) The Network of Sleep Sensors

As all the sensors are in sleep mode, there needs to be a mechanism through which the sensors can be woken up when the target approaches in the region of sleepy sensors.

To wake the sensors up either of the following methods can be used:

a. Prediction Heuristics

In this case most of sensors stay in sleep mode. The current node predicts the future movement and location of the target and correspondingly wakes up the nodes in the region where the target is moving. The critical performance parameters for prediction based reporting are the miss rate and energy consumption. The heuristics reflect the prediction model that can be used for the prediction based object tracking in WSN (Fayyaz, 2011).

b. Sensor Scheduling

Instead of incorporating prediction based scheme sensors can be scheduled for their wakeup and sleep time. In this scheme it is to be determined that which sensors stay in awake over the time in order to have an appropriate trade-off between the tracking performance and the overall sensor usage. The objective is to minimize the estimation errors while still reducing the sensor usage over a period of time (Fayyaz, 2008).

2) Target Reporting

In target reporting only the information target location in terms of Cartesian coordinates is sent to a sink node or some central entity. Thus the data continuously travels through the network. Thus the main task here is to device efficient routing and target location calculation techniques in order to minimize the overall energy consumption by the network and minimizing the tracking error (He *et al.*, 2004).

3) Target Chasing

In target node the sink node has to physically follow the target. Thus the sink node has to continuously consult the neighbouring nodes and the information of target has to be disseminated in the network for sink to follow the target (Fayyaz, 2008).

In this research, the Artificial Fish Swarm Algorithm(AFSA) was used as the target tracking algorithm. AFSA refers to an optimization method simulating fish behaviour. The algorithm imagines a swarm of ‘Artificial Fish’, simulating natural fish’s autonomousforaging behaviour in water, so as to show the advanced ‘artificial intelligence’ behaviour of fish swarm by individual’s simple behaviour and regional interaction. In the optimization process, individual’s and swarm’s regional optimization would tend to be closer to global optimization. AFSA is a random search algorithm, there is no need for the algorithm to collect special information of the problem. It has strong ability to avoid regional optimization as well as rapid convergence (Hong & Zhong, 2014).

2.2.1.3 Type of sensors

The tracking techniques are widely different depending on the type of sensors used as shown in Figure 2.4:

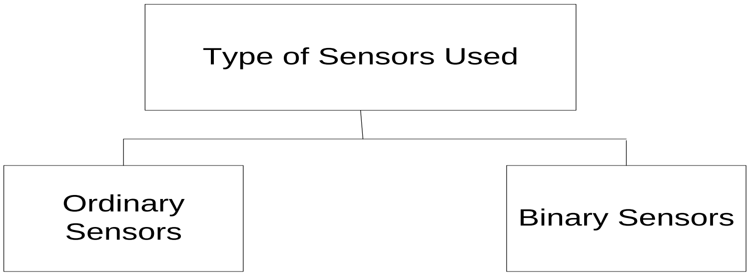


Figure 2.4.Classification of Techniques Based onType of Sensors (Fayyaz, 2011)

1) Ordinary Sensors

The ordinary sensor network consists of the type of sensor nodes that operate on original values of signals. Thus the distance, speed and direction of target have to be calculated on the basis of signal strength measured by the sensor nodes (Fayyaz, 2011).

2) Binary Sensors

The binary sensors work only on two binary values. They can just detect the presence or absence of the target in their sensing range by signalling either by 1 or 0. Thus, the tracking mechanism in this case is more complicated than ordinary sensor networks (Shrivastava*et al.*, 2006).

2.2.1.4 Number of targets used

The tracking technique can be either for single target tracking or multiple target tracking, as shown in Figure 2.5.

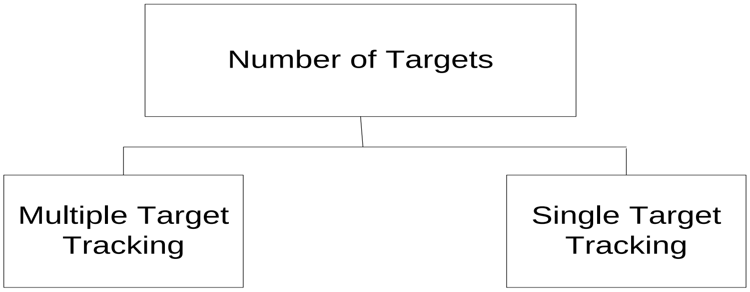


Figure 2.5.Classification of Techniques Based on Number of Targets Tracked (Fayyaz, 2011).

1) Single Target Tracking

Tracking in single target is relatively simple. Less data is produced that results in a low traffic in the network. Less traffic is easier to handle and the routing mechanism is not complex.

2) Multiple Target Tracking

In this case the location of multiple targets has to be tracked simultaneously. Increasing the number of targets to be tracked, increases the network traffic and thus, more complex routing schemes and energy minimization techniques have to be incorporated to compensate for the network performance (Oh *et al.*, 2005).

2.2.1.5 Technology usedfor implementation of tracking in WSN

Various technologies can be used for implementation of tracking techniques in wireless sensor networks including Zigbee, Bluetooth etc (Fayyaz,2011). Mostly the technology which uses omni directional antennas can be used for the implementation of tracking in wireless sensor networks. This is because the presence of the target has to be felt, whatever the direction of motion of target is. The omni directional antennas solve the purpose of tracking (Fayyaz, 2011).

2.2.1.6 Energy efficiency in WSN

One of the major challenges in the design of large magnitude WSN target tracking is the limited availability of power due to the small size of sensor nodes. An efficient energy management can provide a longer network lifetime, since a sensor network lifetime is decided by the power consumed at each sensor nodes (Heinzelman et al, 2000). Usually, the sink node aggregates all the required data and processes them to evolve a trajectory for target. It is often more energy-consuming to let each sensor node directly report to the sink due to different communication ranges. Several energy-efficient data gathering algorithms have been proposed in the literature; the data sensed at each sensor node is forwarded along a communication topology (like a tree rooted at a leader node) in tandem with the data sensed at the other sensor nodes (Meghanathan, 2012).Due to the complexity of sensor node tracking, energy efficiency techniques are implemented either at the node level, protocol or at the application level (Patel & Raval, 2013). Therefore this research focuses on optimal deployment of Sensor Nodes (SN) in order to achieve minimal energy consumption (at level of node) through computational efficiency.

a. Energy efficiency at the level of the node.

   At the node level, attention is focused on the optimal way of deploying the sensor nodes in order to reduce computational power. This is to ensure that the sensor nodes do not stay longer than necessary in the network. Usually, the energy efficiency at this level is determined as a function of time. For example;

   $$E = P \times t \qquad (2.1)$$

   Where *E*, is energy required by the sensor nodes, *P* is the power and *t* the computational time, usually referred to as time to life of the senor nodes.

b. Energy efficiency at the protocol level

   At the protocol level, the focus is to determine the best and shortest routing path for the sensor nodes deployment to ensure quick arrival of nodes. Since there is a limited amount of energy, the routing path needs to be selected in order to ensure efficient energy consumption. Also, the costs associated with computation and communication should be minimum for any protocol being developed.

c. Energy efficiency at the application level

   At the application level, the energy source which is mostly made of battery is designed for optimal and efficient usage.

In this research work, energy management is achieved by designing the appropriate number of nodes, developing reporting mechanism to cluster heads for their measurement outcomes.

2.2.2. Artificial Fish Swarm Algorithm

Artificial Fish Swarm Algorithm (AFSA) is one of the best methods of optimization among the swarm intelligence algorithm (Neshat *et al.*, 2012). This algorithm is inspired by the collective movement of the fish and their various social behaviours. Based on a series of instinctive behaviours, the fish always try to maintain their colonies and accordingly demonstrate intelligent behaviours. Searching for food, immigration and dealing with dangers all happen in a social form and interactions between all fishes in a group will result in an intelligent social behaviour. Advantages of this algorithm include; high convergence speed, flexibility, fault tolerance and high accuracy (Neshat *et al.*, 2012).

The basic idea of the Artificial Fish Swarm Algorithm (AFSA) is to imitate the fish behaviours such as preying, swarming, and chasing(Salawudeen, 2015). The environment where an Artificial Fish (AF) lives is mainly the solution space and the states ofother AFs. Its next behaviour depends on its current state and its local environmental state. An AF would influence the environment via its own activities and its companions' activities (Jiang *et al.*, 2009).

Mathematically, given a swarm with *N*artificial fish such that the state of one artificial fish can be formulated as:

$$X_i = (x_{i1}, x_{i2}, ..., x_{iD})\ for.i = 1,2......N \tag{2.2}$$

Where X_i is the status of the fish, which represent the target variable for the problem under consideration (Wu *et al.*, 2011). The current food concentration in the position of fish is expressed as $y = f(x_i)$ which is the objective function. The visual distance between the artificial fish is $d_{i,j} = \left\| X_i - X_j \right\|$, (2.3)

Where *i* and *j* is a randomly generated fish. *Step* is the maximum size of the movement of artificial fish. δ Is the degree of congestion factor (crowd factor).The basic behaviours offish include:

1) Preying

Preying is a basic biological behaviour that tends to the food; generally the fish perceives the concentration of food in water to determine the movement by vision or sense and then chooses the tendency (Salawudeen, 2015).

Suppose the current state of AF is X_i, the artificial fish select a state randomly within its visual distance such that(Wu *et al.*, 2011):

$$X_j = X_i + rand(0,1) \times visual \tag{2.4}$$

Where X_j is the new state and X_i is the previous state

If $f(X_j) < f(X_i)$ in the minimum problem, it goes forward a step towards X_j in the following direction (Wu *et al.*, 2011).

$$X_i^{(t+1)} = X_i^{(t)} + rand(0,1) \times step \times \frac{X_j^{(t)} - X_i^{(t)}}{\left\| X_j^{(t)} - X_i^{(t)} \right\|} \tag{2.5}$$

If $f(X_j) > f(X_i)$, the artificial fish selects another state randomly again. If the artificial fish cannot meet the requirement in a given time, it moves one step randomly as(Wang & Li, 2015):

$$X_i^{t+1} = X_i^{t} + rand(0,1) \times step \tag{2.6}$$

2) Swarming

The fishes assemble in groups naturally in the moving process, which is a kind of living habit that guarantees the existence of the colony to avoid dangers. Suppose the current state of the artificial fish is, X_i and nf is the number of its fellows within the visual distance, which is equal to the number of elements in the set of $B = \{X_i \mid d_{ij} \leq visual\}$. If $nf \neq 0$, which means the set of element B is not empty, let X_c be the centre position and Y_c stands for the fitness of the centre position. Let $X_c = \sum_j^{nf} X_j / nf$.and $Y_c = f(X_c)$. If $nf \times Y_c < \delta \times Y_i$, the area is not crowded. If $Y_c < Y_i$ the artificial fish moves one step forward towards the companions centre position (Mu'azu *et al.*, 2015).

$$X_i^{(t+1)} = X_i^{(t)} + rand(0,1) \times step \times \frac{X_c^{(t)} - X_i^{(t)}}{\left\| X_c^{(t)} - X_i^{(t)} \right\|} \tag{2.7}$$

Otherwise, executes the preying behaviour. The crowd factor limits the scale of swarms, and more AF only cluster at the best area, which ensures that AF move to optimum in a wide field (Mu'azu *et al.*, 2015).

3) Chasing

When a fish finds food, neighbouring fish will trail and reach the food. Suppose the current state of the artificial fish is X_i, and X_m stands for the best artificial fish individual within $X_i's$ visual distance. nf Is the number of $X_m's$ within the visual distance. $Y_m = f(X_m)$, if $Y_m < Y_i$ and $nf \times Y_m < \delta \times Y_i$ the artificial fish moves one step towards X_m (Mu'azu *et al.*, 2015).

$$X_i^{(t+1)} = X_i^{(t)} + rand(0,1) \times step \times \frac{X_m^{(t)} - X_i^{(t)}}{\left\| X_m^{(t)} - X_i^{(t)} \right\|} \tag{2.8}$$

Otherwise it executes the preyingbehaviour.

Swarming makes few fish confined in local extreme values move in the direction of a few fishes tending to global extreme value, which results in AF fleeing from the local extremevalues. Chasing accelerates AF moving to better states, and at the same time, acceleratesAF moving to the global extreme value field from the local extreme values (Li *et al.*, 2013). The flowchart of the artificial fish swarm algorithm is shownin Figure 2.6.

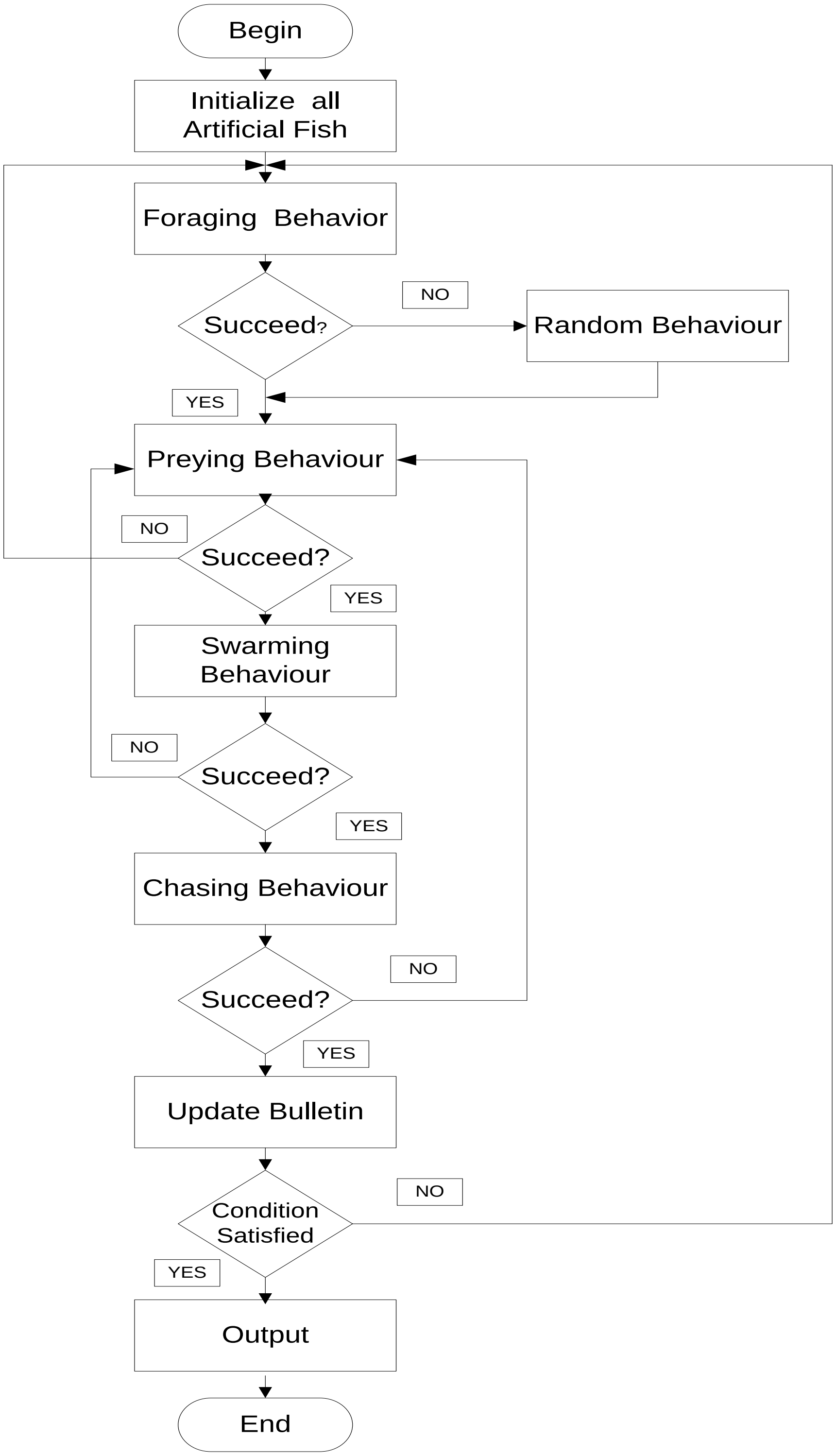


Figure 2.6. Flowchart of Artificial Fish Swarm Algorithm(Salawudeen, 2015).

There are several algorithms reported in literature used for Wireless Sensor Networks, popular among them are the Particle Swarm Optimization (PSO) algorithm based wireless sensor network analysis (Li & Wen, 2015). The velocity solution search equation of the PSO are widely used in WSN. Similarly, Artificial Bee Colony (ABC) algorithm based target tracking has been widely reported in literature (Öztürk *et al.*, 2012).The foraging behaviour of the onlooker and the employee bee can be used as an alternative target tracking algorithm for the wireless sensor network.

However, PSO and ABC have only one solution search equation, unlike the AFSA that has five different solution search equations which effectively guide the algorithm towards global solution. The results from each of the solution search equations in AFSA are compared and the best is passed to the bulletin board. This gives the AFSA a superior performance over most of the swarm based optimization algorithms and hence inspired its choice in this research.

2.3 Review of Similar Works

The following are some of the reviewed literatures relevant to this research.

Tsai *et al.*, (2003) proposed a protocol to track a mobile object in a sensor network dynamically. The work concentrated on the mobile user, and on how to query target tracks and obtain the target position effectively. To track the object quickly and maintain an accurate tracking route, the sensors cooperate together to shorten the route between the target and source dynamically. The proposed scheme, the Dynamic Object Tracking (DOT) protocol was compared with three flooding-based object tracking protocols namely; Threshold Flooding (TF), Schedule Flooding (SF) and Schedule Updating (SU). Experiments were implemented using ns2 simulator and experimental results showed that in TF protocol, the target discovery was similar to DOT but did not maintain the target tracks. In SF protocol, the source performed the target discovery process with a predefined period. In SU protocol, the source broadcasted a query packet. After the first query, the source does not need to query the object tracks by flooding. Because the sensor does not know the location of source, it updates the object's location by flooding. By the simulation results, the proposed protocol had better performance than that of flooding-based query methods. The drawback in this approach is that the broadcast query consumed energy and increased packet overhead.

Malik (2005) worked on target tracking in wireless sensor networks. In the tracking scheme, sensors were deployed in a triangular fashion in a hexagonal mesh such that the hexagon is divided into a number of equilateral triangles. The technique used for detection was the trilateration technique in which intersection of three circles was used to determine the object location. While the object was being tracked by the three sensors, distance to it from a fourth sensor was also calculated simultaneously. The difference was that the closest three sensors detected at a frequency of one second while the fourth sensor detected the object location at twice the frequency. The fourth sensor node was not used for detection but only for estimation of the object at half second intervals and hence did not utilize much power. Using this technique, tracking capability of the system was increased, but not necessarily the accuracy. This is because, two different fourth sensors get activated based on the location of the object at the beginning and end of the time instant and hence, the estimation is not as accurate as in the case where only one fourth sensor would have been selected for location estimation.

Jiang *et al.*, (2008) presented an energy aware sleep scheduling algorithm called Sleep Scheduling in Sensor Networks for Multiple Target Tracking (SSMTT) to support multiple target tracking sensor networks. SSMTT leveraged the awakening results of interesting targets to save the energy consumption on proactive wakeup communication. For the alarm message-miss problem introduced by multiple target tracking, a solution that involved scheduling the sensor nodes sleep pattern was presented. SSMTT was compared against three sleep scheduling algorithms for single target tracking namely; Legacy circle-based proactive wakeup scheme (or CIRCLE), Minimal Contour Tracking Algorithm (MCTA), Target Direction-Based Sleep Scheduling (TDSS). A linear target movement model was introduced as the foundation for energy efficiency optimization. Based on the movement model, a tracking subarea management mechanism and sleep scheduling for nodes was presented. An energy saving approach to reduce the transmission energy for alarm broadcasts was introduced. However, the energy efficiency of the alarm message transmission can be enhanced further with collaboration among the subareas of multiple targets. Experimental evaluations showed that SSMTT achieved better energy efficiency than handling multiple targets separately through single target tracking algorithms. This research work will not be effective on scenarios with multiple target tracking.

Zhang *et al.,* (2009) developed a distributed, self-organization algorithm for ground target tracking using unattended acoustic sensor network. The self-organization algorithm presented in the paper can dynamically select proper sensor nodes to form the localization sensor groups that can work as a virtual microphone array to perform energy efficient target localization and tracking. To achieve this, a time-delay based bearing estimation and triangulation for source localization was used in the sensor network. Acoustic sensor arrays provided means for locating acoustic sources. To demonstrate the source tracking performance of the Self Organization Algorithm (SOA), a simulation was conducted to compare the source tracking performance between the SOA and the closest node method. Kalman Filtering was used to filter the measured target location to achieve more accurate localization. The SOA improved the dynamic target tracking performance. The selection of localization sensor group and the Kalman Filtering effect reduced the tracking error to a level that was far better than the closest node method. However, to have an energy efficient self-organization algorithm, an improvement in the message propagation mechanism is required.

Demigha *et al.*, (2011) proposed a dynamic clustering protocol coupled with a consensus-based Kalman filter algorithm to self-organize WSNs for localized tracking for a single moving target. It considers a WSN with limited sensing range to design a target tracking scheme using low cost limited-energy nodes. In the paper, a Wireless Sensor Network with limited sensing range that localized the "data fusion algorithm" within the target detection zone and self organizes nodes within dynamic clusters that moved along the target trajectory was considered. A Dynamic Kalman Filtering Approach with Dynamic Clustering (DKF_DC) was proposed. Here, instead of tasking all the sensor nodes, it used a dynamic clustering to limit message exchanges between nodes participating in the estimation process. TOSSIM was used to validate the method. TOSSIM is a discrete time simulator of Tiny Operating System for Wireless Sensor Motes. The method was compared with three different target tracking schemes: Centralized Kalman Filter (CKF), Distributed Kalman Filter with Limited Sensing Range (DKF_LSR) and Distributed Kalman Filter with Gossip Communications (DKF_GOSSIP). The CKF was considered as the base reference for comparison. Simulation parameters that were varied are the sampling period, the network size (or network density), the target velocity. The Distributed Kalman Filtering method coupled with dynamic clustering protocol (DKF_DC) helped at reducing the network energy consumption but the estimation quality was 'slightly' degraded.

Hassani *et al.*, (2011) presented a new fuzzy-logic based adaptive Interactive Multiple Model (IMM) filter for tracking a vehicular rotating object in a Wireless Sensor Network (WSN). A Fuzzy-logic Inference System (FIS) was employed to adaptively tune the system noise covariance matrix associated with the Nearly Constant Velocity (NCV) model. By reducing the number of interacting models, the algorithm simplified state-of the-art IMM algorithms for tracking of a rotating object. Localization for data aggregation process was performed by means of the triangulation method in conjunction with dynamic grouping of sensors. Monte Carlo simulations showed that the scheme achieved good tracking performance for both highly rotating and non rotating objects compared to state-of-the-art IMM algorithms in terms of accuracy and efficiency. The major drawback in this approach is that it is computationally tasking.

Charanya& Uma, (2012) proposed an energy efficient prediction-based clustering algorithm to track the moving object in wireless sensor network. This algorithm reduced the number of hops between transmitter and receiver nodes and also the number of transmitted packets. In this method, the sensor nodes are statically placed and clustered using LEACH-R algorithm. The prediction based clustering algorithm was applied where few nodes are selected for tracking which used the prediction mechanism to predict the next location of the moving object. The current location of the target is found using Trilateration algorithm. The current Location or predicted location is sent to active cluster head from the leader node. Based on which node send the message to the cluster head, the predicted or current location will be sent to the base station. Energy efficient prediction based clustering algorithm, reduced the average energy consumed by sensor nodes and thereby increase the lifetime of the network. The experiment was carried out using Network Stimulator-2 environment. Simulation results showed that the proposed algorithm gave a better performance and reduced the energy consumption. In the research work, only single target tracking was however, considered.

Yiyue*et al.*, (2012) proposed a wireless sensor network deployment using an optimized artificial fish swarm optimization algorithm. The artificial fishes are considered as wireless sensor nodes to be optimized and a dynamic threshold was introduced to improve the convergence speed of the AFSA. Simulation results show that the proposed method can improve the network coverage efficiency and performed better than most of the wireless sensor network deployment techniques. However, the proposed method only considers static sensor nodes which do not guarantee an efficient deployment in a dynamic environment. Similarly, energy efficiency (in terms convergence speed) of the proposed technique does not improve when compared with existing method.

Zhao & Sun, (2012) proposed an intelligent single particle optimizer based wireless sensor networks' deployment for adaptive coverage. The probability model measurement characteristics of wireless sensor node were used to adaptively determine the optimal deployment of sensor nodes based on intelligent particle optimizer. Simulation result shows that the method has better coverage performance than the standard particle swarm optimization. However, in their work they did not consider the effect of attenuation factor on the sensor network.

Öztürk *et al.*, (2012) proposed and Artificial Bee Colony (ABC) algorithm based dynamic deployment for wireless sensor network. ABC was used for the deployment of mobile sensor network to enhance performance by increasing the coverage area of the network. Simulation result shows that the proposed scheme can be utilized in a dynamic deployment of wireless sensor network. In this research work, the effect of attenuation factor was not considered.

Li *et al.*, (2013) proposed a scheme for harmful acoustic signals recognition and localization based on AFSA for Wireless Sensor Network. They optimized the coverage were the harmful sound source can be detected and determined the eigen value of the harmful acoustic signal by Linear Prediction Coefficients (LPC). The harmful sound was detected by analyzing the similarity between the eigen value and data pre-stored in the data base. The harmful resource was located with the help of its closest nodes which were chosen based on time delay. Gunshot was chosen as the harmful acoustic signal. Simulation was carried out using MATLAB. The proposed scheme was based on localization and detection, but energy efficiency was not considered.

Wang & Wang, (2013) estimated the target detection probability by single-node processing based on particle filter. A dynamic node selection scheme based on genetic algorithm which can optimize the tradeoff between the accuracy of tracking and the energy cost of nodes was used. MATLAB was used as the simulation platform. A node selection scheme was proposed which gives full consideration to both the information utility and the remaining energy of nodes. The goal of the scheme was to select the optimal set of sensors in order to achieve a good balance between the accuracy of localization and the energy cost of sensor nodes. Each sensor nodes, respectively, implemented the target sensing by computing the detection probability, whereas the optimal set of sensors performed target tracking by integrating partial estimations. Each node in Wireless Sensor Networks separately implemented the target tracking based on particle filter.

The number of selected sensor nodes for target tracking is four at most, which implied that the size of the optimal set is small. Accuracy of localization and energy efficiency of node selection were evaluated respectively using the Root Mean Squared Error (RMSE) and the energy cost. The proposed scheme was compared with the three schemes and the comparison was on the basis of results averaged over 50 independent runs. The problem of node selection was formalized as an optimization problem and solved through genetic algorithm. The scheme was evaluated by comparing it with several methods and examining the influence of different parameters on the process of node selection. Experimental results showed that the proposed scheme could achieve energy saving and at the same time preserve a tolerable tracking error. However, the energy cost was not properly addressed, because it tends to increase as the tracking accuracy increased.

Wang *et al.*, (2013) proposed a novel mobility management protocol called Hybrid Cluster-Based Target Tracking (HCTT), which integrated on demand dynamic clustering into a Cluster-based Wireless Sensor Network for target tracking. By constructing on demand dynamic clusters at boundary regions, nodes from different static clusters that detected the target can temporarily share information and the tracking task can be handed over smoothly from one static cluster to another. As the target moves, static clusters and on-demand dynamic clusters alternately manage the target tracking task. However, static cluster membership prevented sensors in different clusters from collaborating and sharing information with each other. Thus, causing a 'boundary problem' when the target moved across or along the boundaries of clusters. Boundary Problem resulted in the increase of tracking uncertainty or even the loss of target. Therefore, a new protocol is required to solve the Boundary Problem and realize a tradeoff between energy consumption and local sensor collaboration for cluster-based sensor networks. The HCTT integrated on-demand dynamic clustering into a scalable cluster-based Wireless Sensor Network with the help of boundary nodes which facilitated sensors collaboration among clusters to solve the Boundary Problem. Sensor nodes were organized as static clusters according to the LEACH protocol. The performance of HCTT was compared with DPT, DCTC and ADCT. DPT was the most energy efficient target tracking approach but suffers boundary problem which resulted in a high probability of missing the target. HCTT is not the most energy efficient scheme, as there is a tradeoff between the energy consumption and missing probability or sensing coverage.

Yang & Yong, (2013)proposed a short life artificial fish swarm algorithm for wireless sensor network based on active sleeping nodes. Multiple visual of AFSA was used to detect events based on the intelligent behaviour of fish. Simulation result demonstrated that the algorithm can effectively improve the network coverage as compared with similar algorithm. However, in this work, only the searching (swarming) and chasing behaviours of fish was considered.

Zhao *et al.*, (2014)proposed a search control approach for cooperative under water wireless sensor network based on artificial fish swarm algorithm. A fish-swarm based algorithm was designed requiring local information at each fish node and maximizing the joint detection probabilities of distress signals. Optimization formation was also considered for the searching control approach and was optimized by fish-swarm algorithm. Simulation results include two schemes: preset route and random walks, and it showed that the control scheme had adaptive and effective properties. The drawback in this work is that network coverage was not considered as metric for determining the reliability of the proposed scheme.

DaWei&Changliang, (2015) proposed wireless sensor networks coverage optimization based on Improved AFSA Algorithm. Node utilization and effective network coverage was set as the optimization goals. An inverse Gaussian mutation algorithm was introduced into the AFSA as a form of improvement on the standard AFSA and the improved AFSA was used for the deployment of the formulated WSN optimization problem. Simulation result shows that the proposed model can improve the effectiveness of WSN coverage. However, the effect of attenuation factor was not considered.

Ma & Xu, (2015) proposed an energy distance aware clustering protocol with dual cluster heads using niching particle swarm optimization for wireless sensor networks. In this research work, two cluster heads were selected in each cluster, the Master Cluster Head (MCH) and the Slave Cluster Head (SCH), and the selection were made to consider the network state information carefully and deliberately. Simulation result shows that the proposed model can extend network life time. However, the research work did not consider network coverage and the effect of attenuation factor on the sensor network.

To overcome the limitations mentioned above, an Artificial Fish Swarm Algorithm will be used in localization and detection of targets and also improve the energy efficiency. Each Artificial Fish (AF) will represent a sensor and the coordinate of the artificial fish will represent the position of the sensors. The AFSA will optimize the system by simulating fish actions, such as preying, swarming and chasing.

CHAPTER THREE

MATERIALS AND METHODS

3.1 Introduction

In this chapter, the detailed procedure adopted and all the relevant mathematical models necessary for the successful completion of this research are presented.

3.2 Wireless Sensor Network Model

The wireless sensor network (WSN) considered in this research consists of fixed and mobile sensor nodes. 60 fixed nodes were randomly generated in a coverage area of $60m \times 60m$. The numbers of fixed and mobile sensor nodes are assumed to be *N* and *D* such that the collection of all the nodes in the network can be represented as:

$$W = \{W_1, W_2, ...W_i, ...W_{(N,D)}\} \quad (3.1)$$

Where $W_i$represent the i^{th}node in the network. Assume that *M(x, y)* is a random point in the network coverage area and a certain node $Q(x_i, y_i)$ is within the monitored area. Then the distance between the nodes is:

$$X(M,Q) = \|Q - M\| = \sqrt{(x_i - x)^2 + (y_i - y)^2} \quad (3.2)$$

The probability measurement model was used for the detection probability of nodes *Q* by node *M*

$$P_p(Q_i) = \begin{cases} 0 & R_s + R_e \le X(M,Q) \\ e^{-\alpha\lambda^{\beta}} & R_s - R_e < X(M,Q) < R_s + R_e \\ 1 & R_s - R_e \ge X(M,Q) \end{cases} \quad (3.3)$$

Where $R_s$is the perceived radius of various elements in the network, Re is the uncertain factor within the measurement range of the nodes. $0 < R_e < R_s$; α and β are measured parameters related to the physical devices; λ is the input parameters defined as(Zhao *et al.*, 2014):

$$\lambda = X(M,P) - (R_s - R_e) \tag{3.4}$$

Therefore the joint detection probability of multiple sensor nodes conducting measurement simultaneously was formulated as (Yang & Yong, 2013):

$$P_p(Q) = 1 - \prod_{w_i \in W} \left(1 - P_p(Q,M)\right) \tag{3.5}$$

The program for the detection probability is presented in Appendix B.

3.3 Network Coverage Area

Network Coverage Area (NCA) is an important index to measure the strategy of the wireless sensor network deployment. In this research, the NCA is considered as the ratio of the whole area that can be covered by the nodes in the total area of node-aware and the total area of the monitoring region. Considering the complication of monitoring environment, the probability measurement model described in equation (3.3) was adopted in this research. To minimize energy consumption, the following assumptions was made in this study.

a) Network nodes are ideal (i.e. nodes in the network have the same communication radius R_c and the same sensor radius R_s and $R_c>2R_s$ because when communication radius between nodes is greater than two times the sensor radius of nodes, then the current networks are connected)
b) Coverage is considered as the measure of quality of service of a sensor network(Zhao *et al.*, 2014).

c) At the initial stage of network deployment, the nodes are randomly distributed in a square monitoring area whose length is N, the coordinate range of the monitoring area is from *(0, 0)* to *(N, N).* Then the nodes obtain coordinate position information of its own and its neighbours.

d) During the algorithm, the movement of the nodes are virtual. After the end of the algorithm, nodes move to the best locations on the physical location for one time, in order to reduce consumption of energy(Zhao *et al.*, 2014).

e) The model and physical structure of each node are the same(Li *et al.*, 2013).

3.3.1 Network Area Problem Formulation

The total number of nodes (which is represented as a randomly generated artificial fish) was first defined as *N*. *H* and *H'* are set of total nodes and set of active nodes respectively. The inspection region of *H* and *H*' are correspondingly *G* and *G'*. The i^{th}node inspect region is G_i. The network coverage area is formulated as follows:

$$\omega(H') = \left(\frac{H'}{N}\right) \tag{3.6}$$

The quality of the network coverage area is defined as follows:

$$C(H') = \frac{\bigcup_{i=1,2,\ldots N} G_i}{G} \tag{3.7}$$

From equation (3.7), the objective function of the coverage quality is formulated as follows:

$$\max[F(H')] = C(H') \tag{3.8}$$

The network region optimization was extracted into solving the optimization problem with equation (3.8) as the objective function.

3.4 Optimization Using Artificial Fish Swarm Algorithm

As discussed in Section 2.2.2 of chapter two, AFSA is an optimization algorithm which works based on the population and stochastic search behaviours of fish. AFSA uses the preying, swarming and chasing behaviours of fish to find the optimum solution to optimization problems. In this research work, the AFSA consists of mobile nodes (cluster of nodes), in which the cluster head node travels in accordance with the objective function. All nodes are processed in accordance with the artificial fish swarm algorithm to ensure that the whole fish swarm maintains a reliable communication and maximum search scale.

Assuming in an *n*-dimensional target tracking search space, there is a swarm of fish consisting of *N* AF, and the state of individual AF is expressed as $W = \{w_1, w_2, ..., w_n\}$ in which $w_i = (i = 1, ..., n)$ are the variables which need to be optimized. The food concentration (which is target to be tracked) of AF's current location is expressed as $Y = f(W)$ where *Y* is the objective function. The distance between any individual AF is expressed as:

$$d_{ij} = \|W_i - W_j\| = \sqrt{(Wi - Wj)^2} \tag{3.9}$$

In water, fish moves randomly seeking for food and companion in larger ranges. The basic behaviours of AF is to choose a state randomly within its visual distance and then moves towards this state using equation (3.1). The preying, swarming and chasing behaviours of AFSA described in equations (2.4) to (2.8) are utilized to draw the nodes closer to the cluster heads. In order to maintain maximum search range, the crowd factor and the distance between fishes is used to ensure that the AFSA maintain good information. When the artificial fish swarm algorithm (AFSA) is either in preying, swarming and chasing mode, it goes back to the random behaviour and then continues the iteration process until the best solution is found.

In order to increase the response accuracy of the communicating nodes (AF), multiple communicating nodes are supported in AFSA.

3.4.1 Random Behaviour inWSN

The random behaviour allows the Artificial Fish (nodes) to moves smoothly in the network. For example, if the current location of artificial fish within the visual distance is $W_i$and there are no artificial fish (nodes) within this range of vision, then artificial fish will execute the random behaviour described in equation (2.3). The unvisited nodes within the artificial fish's visual distance are $N_{i,}$ then artificial fish chooses any node randomly from $N_i$as target and moves to the nodes.

3.4.2 Preying inWSN

The ability of artificial fish (AF) to detect the concentration of food in water and then moves quickly towards this region is utilized to detect the location of nodes (target) in this research. The detail of the procedure and all relevant mathematical model describing this behaviour is presented in subsection 2.2.2.

3.4.3 Swarming in WSN

The fishes assemble in groups naturally which is a living habit that guarantees the existence of the colony in order to avoid dangers. The crowdedness degree is used to limit the swarming scale, this give room for more nodes to cluster in the best area which ensure an optimum solution in a wide area. Detailed information about this behaviour can be found in Subsection 2.2.2.

3.4.4 Chasing inWSN

As discussed in Subsection 2.2.2, when the artificial fish find food, neighbouring fish will trail and reach the food. In order to increase the accuracy of the nodes responses, the chasing behaviour of fish is used to make cramped network node in local extreme values to move in the direction of a few network nodes (Fish) tending to global extreme value. By this, Chasing makes network nodes to accelerate faster towards better state and improves the probability of the node (Fish) moving to the global extreme value.The program for the artificial fish swarm algorithm used for the wireless sensor network in this research can be found in Appendix A.

The visualization principle of artificial fish swarm algorithm is as given in Figure 3.1

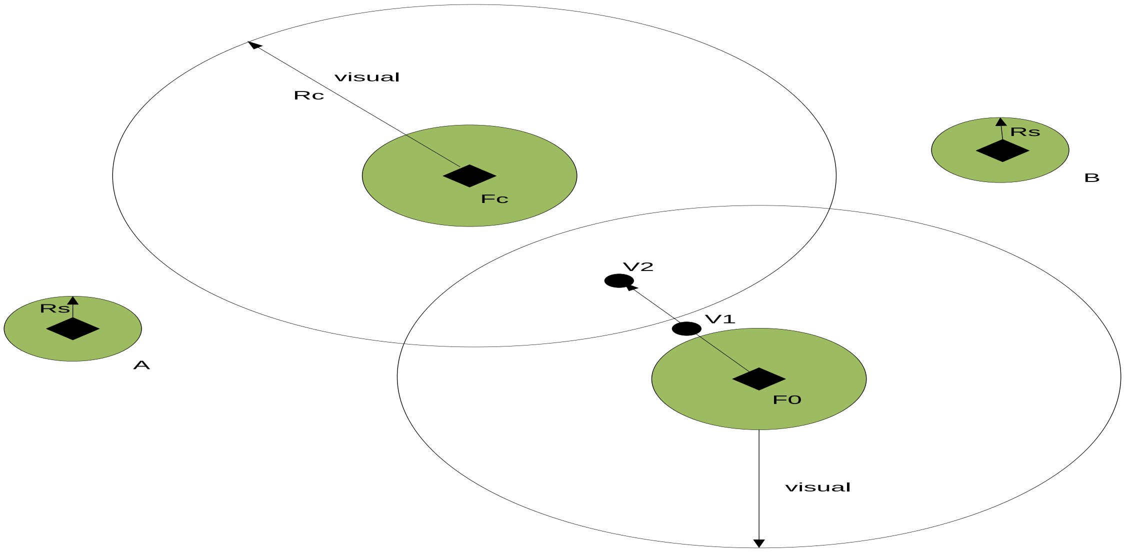


Figure 3.1. Geometric Visualization Principle of Artificial Fish

As shown in Figure 3.1, the Artificial Fish perceived the external nodes (A and B) using the information about its visualization. As indicated in the figure, F0 is the position of an artificial fish, Fc is the crowded position and V2 is the visual position at a particular point. If the position at this visual is much better than the present position, the artificial fish goes forward a step in this direction towards the V1's position otherwise it continue the search within its vision. The geometric diagram showing the network coverage for 4 nodes is shown in Figure 3.2.

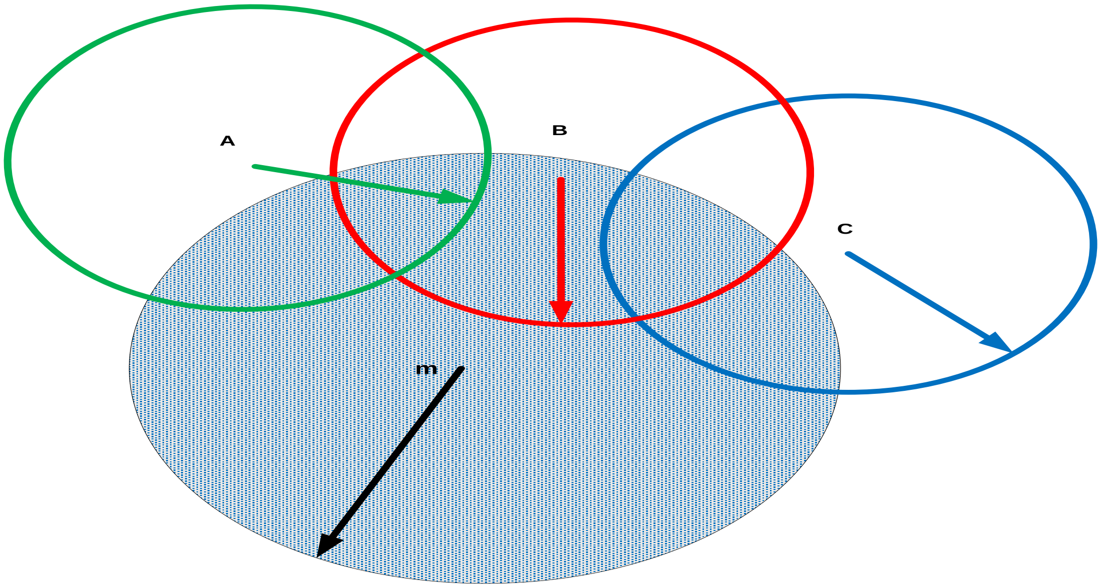


Figure 3.2.Geometric Diagram of Network Coverage for 4 Nodes

As shown in Figure 3.2, the monitored node is represented as m, while A, B and C are the neighbouring (perceived) nodes. Direct communication between the nodes exists, when the nodes intersect within the connection region of one another. Assuming the monitored node m is subdivided into N number of circles and a random circle ρ is selected from N; the network coverage for this is

$$N_c = \frac{N\left\{\min\left\{P_{\rho\in\left(\mathrm{A}\cap\left(\mathrm{A}\cup\mathrm{B}\right)\cup\mathrm{C}\right)}(S_1, S_2, S_3)\right\} \geq d_{th}\right\}}{N} \tag{3.10}$$

d_{th} is the threshold value of the detection probability while the entire numerator represents the number of nodes that satisfy this threshold value. N is the total number of sub-circle. S_1, S_2, S_3 are the sensor nodes for the perceived regions A, B and C.

The adopted procedures for the proposed method are given as follows:

i) Initialize the wireless sensor nodes and select the appropriate parameters for the Artificial Fish Swarm Algorithm (*Visual distance*, *Step size*, *crowd factorand maximum iteration number*)

ii) Initialize the population of AFSAW randomly which represent the coverage area's dimension of the network and initialize the iteration to $itr = 0$

iii) Calculate the fitness of the current locations in the swarm Y_i (the network coverage Y_i) and update the score board with the best individuals.

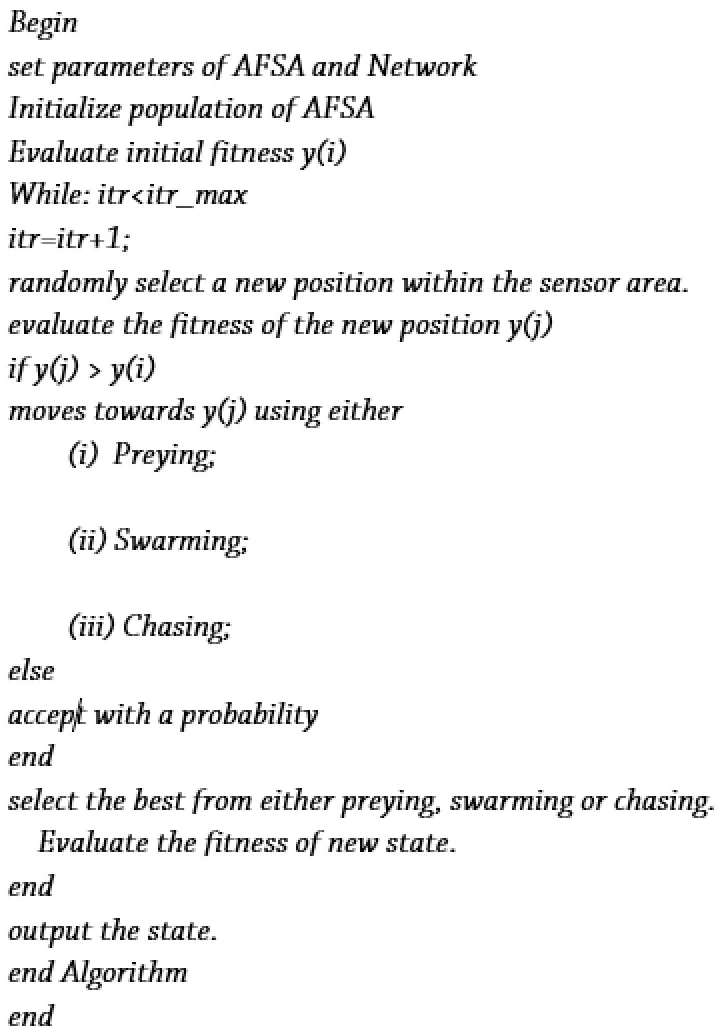
iv) Select a new state $W_j$randomly using equation 2.2 and evaluate its fitness Y_j

v) Execute the three (Preying, Swarming and Chasing) behaviours of Fish as discussed in section two and update the score board with the best artificial fish found so far.

vi) Evaluate the fitness of the current population (Nodes) and compare with the previous fitness and update the score board with the best result.

vii) If the termination criteria is met output the current fitness value in the score board (which is the optimum solution); if not increase iteration by 1 and go back to (vi) until the best solution is found.

The pseudo code description of the optimization of Wireless Sensor Network (WSN) using the Artificial Fish Swarm Algorithm is given as follows:



```
Begin
set parameters of AFSA and Network
Initialize population of AFSA
Evaluate initial fitness y(i)
While: itr<itr_max
itr=itr+1;
randomly select a new position within the sensor area.
evaluate the fitness of the new position y(j)
if y(j) > y(i)
moves towards y(j) using either
    (i)  Preying;

    (ii) Swarming;

    (iii) Chasing;
else
accept with a probability
end
select the best from either preying, swarming or chasing.
  Evaluate the fitness of new state.
end
output the state.
end Algorithm
end
```

The complete code for the algorithm which is implemented in Matlab R2013b can be found in appendix A. The flowchart implementation of the complete algorithm is as shown in Figure 3.3.

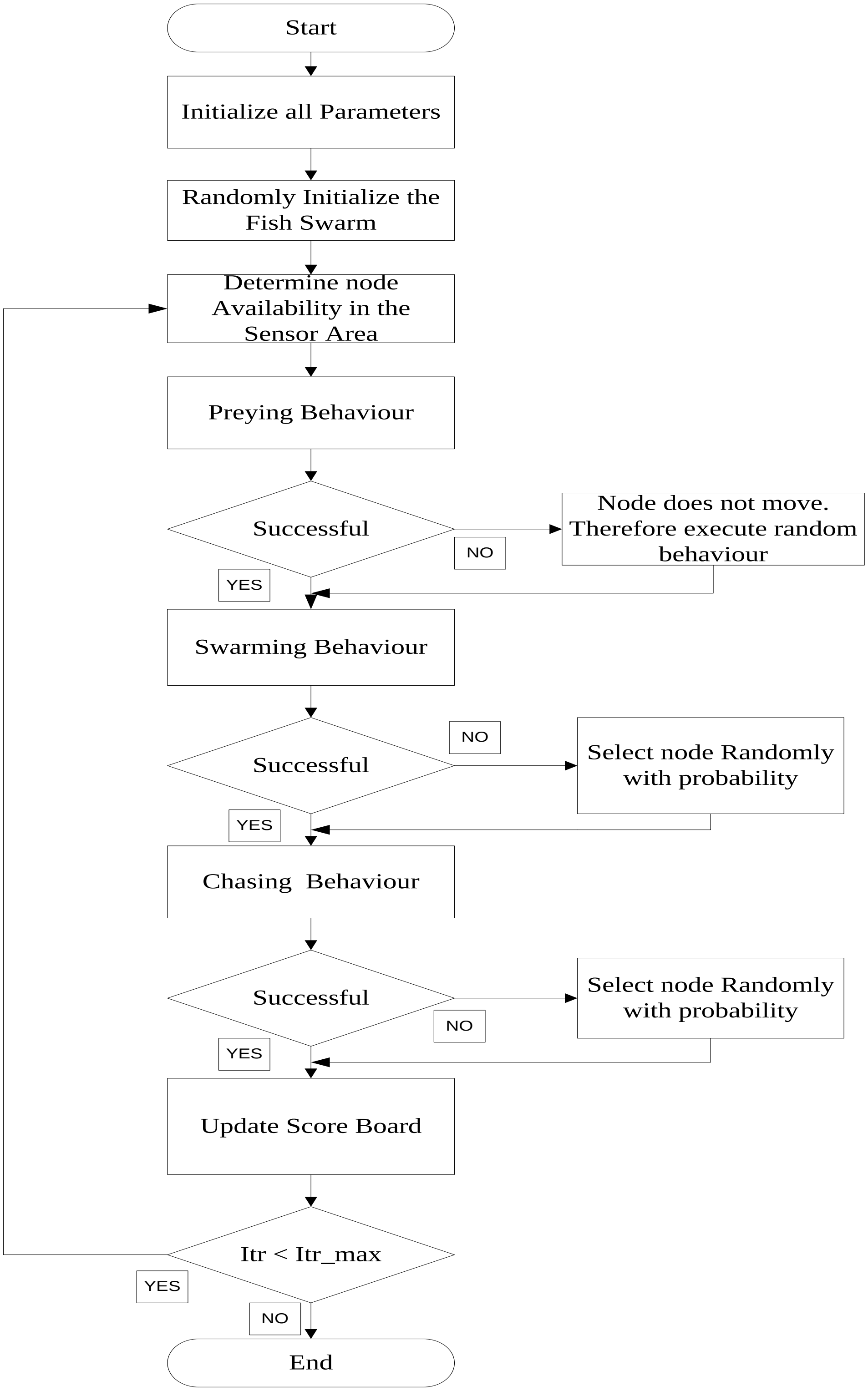


Figure 3.3. Flowchart of the Wireless Sensor Network Using AFSA

3.5 Target Formation Using Mobile Nodes

The aim is to locate particular targets (nodes) from a set of mobile network nodes *N*. In order to achieve this, the following assumptions were made in this research:

- i) Unlimited number of targets (mobile nodes) can be tracked. But, for the purpose of validation, a maximum of 60 targets were used in this research.
- ii) Targets can be tracked in four different locations within the network coverage area (Depending on their communication range and distance apart)
- iii) The numbers of nodes tracked in each location are independent of each other.
- iv) Targets can change location (where necessary) during tracking (i.e. new target may show up).
- v) When a target is tracked, neighbouring target within the coverage region (Visual distance) is automatically tracked.

In this research, the frequency that a node can survive at a target point is $\rho(x)$. The condition for survival of these nodes is to satisfy $0 < \rho(x) \leq n$ where x are set of mobile nodes $x \in A$(Ehsan & Hamdaoui, 2012). *A* is the total number of nodes within the coverage region and *n* is the maximum number of targets to be tracked. To determine which target to track at a particular time *t*, each target is assigned a particular function $\Gamma_j\Phi_j(\;)$ where Γ_j is the maximum tracking time of the targets and $\Phi_j(\;) \in [\;,1]$ is the limit of occurrence which is associated with Γ_j over time. The limit of occurrence associated with a particular target is determined as follows(Zhao *et al.*, 2014):

$$\Phi_j(t) = \begin{cases} 1 - \frac{\mu_j}{H_j} t & t \le H_j \\ (1 - \varepsilon_j) e^{-\eta_j (t - H_j)} & t > H_j \end{cases} \tag{3.11}$$

Where H_j is the limit of occurrence for target point *j* and $\varepsilon_j \in (0,1)$, $\eta_j > 0$ are target specific parameters. An optimization problem is formulated for the limit of occurrence of target nodes as follows(Demigha *et al.*, 2013):

$$\tau_{opt} = \max \int_A \Gamma_j \Phi_j (A) \rho (A, P_A(B)) F(A) dA \tag{3.12}$$

From equation (3.12), $\Gamma_j \Phi_j (t)$ indicate that the limit of occurrence by targets in *A*, reduces with the discounting function, $\rho(A, P_A(B))$ is the detection probability of the targets in area *A* by all targets in set *B* and $F(A)$ is the node trajectory equation in *A*(Li & Wen, 2015). The aim is to track a particular number of targets from *T*targets using an *N*number of nodes. In this research, it is assumed that the S denotes the *T*targets such that $S = \{t_j \mid j = 1,2,..., T\}$ and that *U* denotes *N* numbers of nodes, such that $U = \{n_i \mid i = 1,2,..., N\}$.

3.6 Energy Efficient Management

As discussed in subsection 2.2.1.6, all the queried data are aggregated by the sink and then processed to evolve a trajectory for the target.This may cause a significant increase in energy, if each sensor nodes are allowed to report to sink for every time unit. Therefore, this research considered the entire WSN as swarm of Artificial Fish (AF) such that, data sensed at each sensor node is forwarded along a communication protocol or topology in tandem with other data sensed at the other sensor nodes.This will enable each sensor nodes to simply sum up the strength of the signal sensed in its neighbourhood for a period of time, thereby reducing time ofenergyconsumed by individual nodes. Since the activities of individual nodes is to be as low as possible in order to minimize energy consumption. In order to achieve this, an appropriate population of sensor nodes is selected.

3.7 Model Parameter Setting

Although the model was made user dependent, but for the purpose of validation, the parameters shown in Table 3.1 was adopted.

Table 3.1.AFSA and Network Parameters

SN:	Parameters	Definition	Values
1	Visual	Visual Distance of Artificial Fish	20m
2	Step	Step Size of Artificial Fish	10m
3	Crowd	Crowd factor of Artificial Fish	0.6
4	N	Number of Artificial Fish (Mobile Node)	60
5	Rs	Sensor Radius	4m
6	Rc	Commutation Radius of the Nodes	15m
7	R	Uncertain Factor in the measurement	2m
8	Try_num	Number of trial	60
9	Kmin	Cessation Value of AFSA	40
10	K	Current Value of AFSA	Iterative
10	K_0	Initial value of AFSA	200
11	r	Attenuation constant	0.95
12	Pm	Measured probability	0.8
13	k	Actuation Constant	0.4
14	q	Cluster Size	20m

3.8 System Specification

The simulation was carried out on COMPAQ Presario CQ56 computer system with the following specifications.

a) Processor : Intel(R) Celeron(R) 2.20GHz

b) Random Access Memory (RAM): 3.00GB

c) Operating System (OS): 64-bit Windows 8 pro

d) Mother Board Speed: 2.20GHz.

e) Dedicated Video Graphics : 64M

The WSN model was developed and Target tracking technique was also developed considering energy efficiency management. It is shown empirically that AFSA provides better solution than other algorithms. The global searching ability of AFSA is improved and the solving efficiency is optimized.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Introduction

In this chapter, the performance of the proposed wireless sensor network using the artificial fish swarm optimization algorithm is presented. The model is developed and simulated using the Matlab2013Rb simulation environment.

4.2 Performance Evaluation of the proposed WSN model Based on Variation between Coverage Area and Sensor Nodes

One of the most important metric usually considered as a measure of quality of service in wireless sensor network is the network coverage. In other to evaluate the performance of the proposed model, 60 wireless sensor nodes were randomly deployed and the problem dimension of 60 was used. Therefore, the target coverage area was made 60×60 square meters. This specification was employed for all the simulation carried out in this research. All the Artificial Fish Swarm Algorithm parameters and all the network parameters have been detailed in Table 3.1.To establish the relationship between the coverage area and the sensor nodes, the total number of nodes was kept at 60nodes while the change of network coverage was determined at every 5 nodes. Figure 4.1 shows the graphical representation of the relationship between the network coverage and the network nodes.

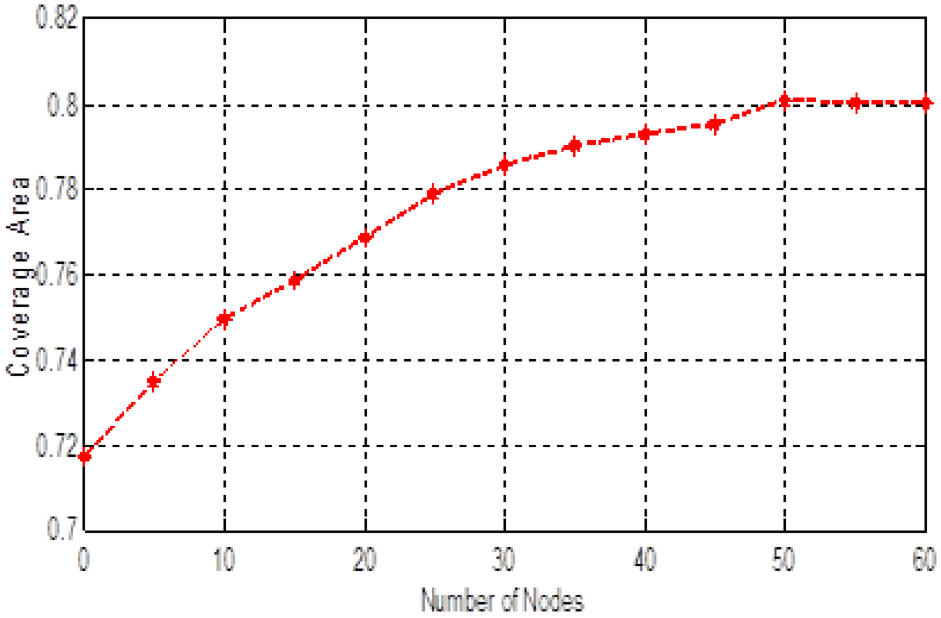


Figure 4.1. Relationship between Network Coverage and Network Node.

From Figure 4.1, it can be seen that the network coverage changes (increases) with increase in number of network nodes. The network coverage attains its maximum (which is 80.13%) when the number of network nodes is 50. Thereafter, tends towards stability when the number of network nodes is above 50.

4.3 Performance Evaluation of the proposed WSN model Based on Variation between Coverage Area and Number ofIteration

To establish the relationship between the network coverage and the number of iterations, the average value of network coverage after every five iteration is recorded.Figure 4.2 shows the graphical relationship between the network coverage and number of iteration.

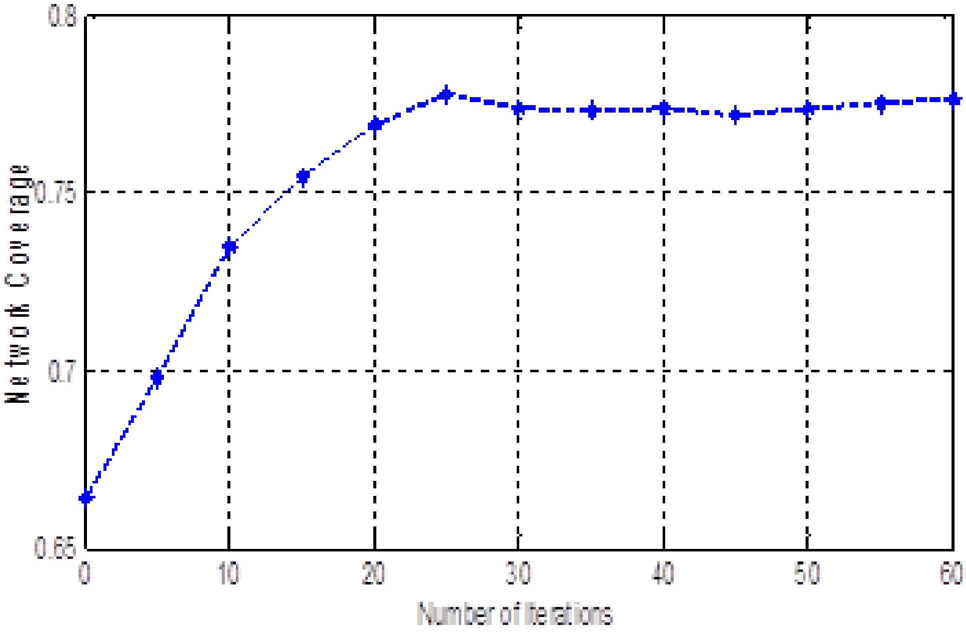


Figure 4.2.Relationship between Network Coverage and Number of Iterations

To evaluate the performance of the proposed model, network coverage was monitored after 5 iterations up to 60 iterations. Figure 4.2 shows that, the network coverage changes with change in iteration. TheAFSA was able to reach a maximum value of 77.87% of network coverage when the number of iteration is 25. After the network coverage reaches its maximum at 25 iteration, it kept almost the same value up through to the last final iteration.

4.4Performance Evaluation of the proposed WSN model Based on Variation between Network Coverage and Number of Mobile Nodes at Different Attenuation Factor

To evaluate the effect of attenuation on the performance of the network, the average value of network coverage after every five iteration through 60 iterations is recorded.

Figure 4.3 shows the graphical relationship between the coverage area and number of iteration, for the various attenuation factors considered.

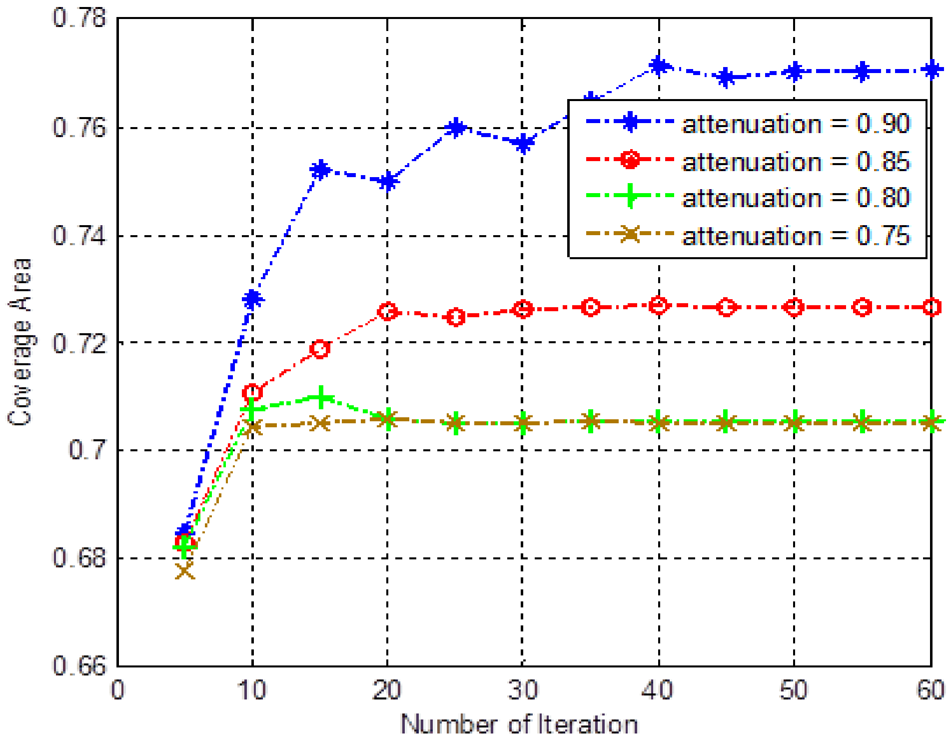


Figure 4.3: Effect of Attenuation Relationship between Network Coverage and Number of Iteration.

It can be observed from Figure 4.3, that when the attenuation factor is 0.75 the network coverage attains its maximum at 70.58% thereafter become stable all through the simulation process. When the attenuation factor is 0.80 the network coverage attains its maximum at 70.99%for 15 iteration, thereafter becomes stable at 20 iteration and all through the simulation process. For attenuation factor of 0.85, the maximum coverage attained by the network is 72.69% which occurs at 40 iterations. Similarly, the maximum network coverage of the network when the attenuation factor is 0.90 is 77.15% which occurs when the number of iteration is 40.The minor difference in the network coverage (maximum and minimum) indicates the model converge and therefore has improve the scalability of the Wireless Sensor Network (WSN) model.

4.5Target Tracking Simulation Scenarios

In this subsection, the simulation processes of target tracking are presented. Snippets of the Matlab simulation were taken at the initial stage of simulation, 4 second into simulation and at the end of the simulation process. This are presented in Figures 4.4, 4.5 and 4.6 respectively.

1. Simulation scenario showing the initial positions of nodes (targets) before tracking

Figure 4.4 shows the randomly generated initial position of targets (mobile nodes) before tracking. As detailed in subsection 3.4, targets within the visual distance of each locations (A, B, C, and D) are tracked. Figure 4.4 depict the snippet of the initial positions of targets simulation process.

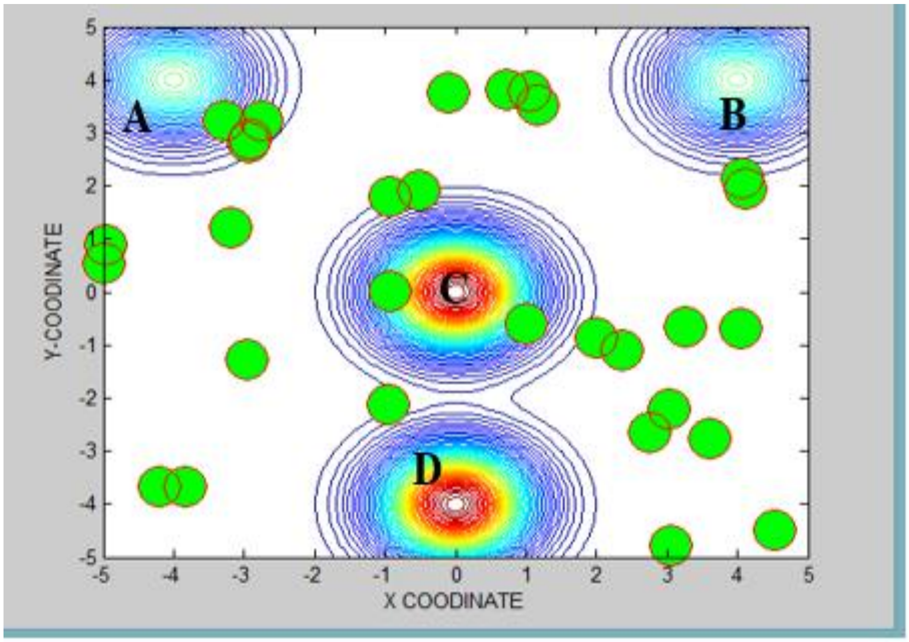


Figure 4.4: Initial Positions of targets

From Figure 4.4, it can be observed that the 30 mobile nodes (targets) are initially positioned randomly. And will eventually be tracked into positions A, B, C and D.

1) Simulation scenario showing the position of the nodes (targets) after 4 second

Figure 4.5 shows the current positions of the targets, 4 second into the simulation. It is expected that all the nodes are tracked towards the target positions which could be any of the four (A, B, C and D) location.

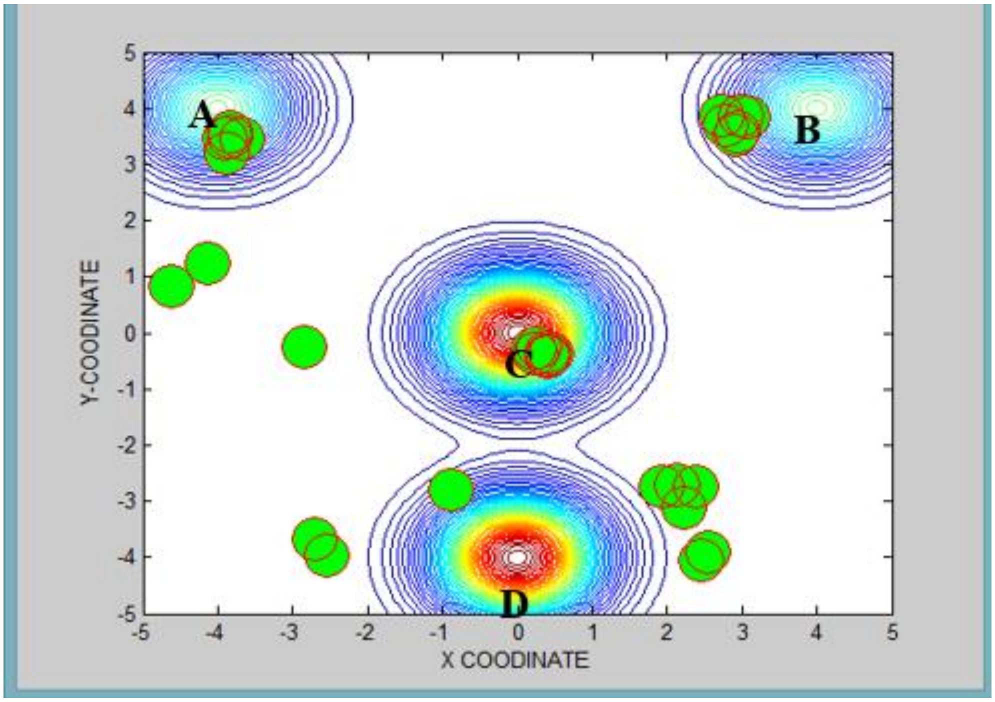


Figure 4.5: Targets positions after 4 second

From Figure 4.5, it can be observed that the targets are tracked into the target locations based on their various distances (visual) apart.

2) Simulation scenario showing the position of the nodes (targets) after 4 second

Figure 4.6 shows the final position of the targets at the end of the simulation process. After 50 iterations, all the 30 randomly generated targets (nodes) are tracked at their various target locations.

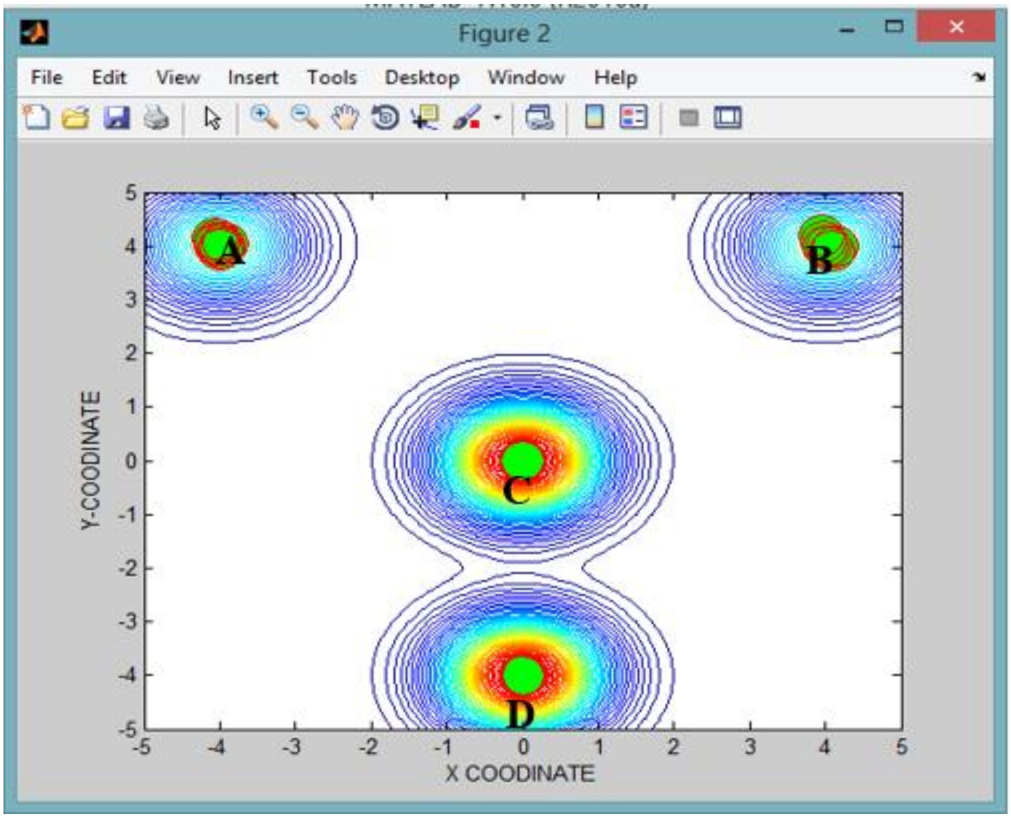


Figure 4.6: Final position of the targets

From Figure 4.6, it can be observed that, at the end of the simulation process (after 50 iterations), all the targets (30 mobile nodes) were successfully tracked based on their visual positions. In order to efficiently track the targets while minimizing energy consumption, a trade-off has to be made between the number of nodes and time of computation.

4.6 Time of Target Discovery and Number of Targets

The bar chart presented in Figure 4.7 shows the relationship between the total time of tracking and the number of targets tracked. The highest bar, depict the overall tracking time when the number of target is 15 while the shortest bar depict the overall tracking time when the number of targets is 60.

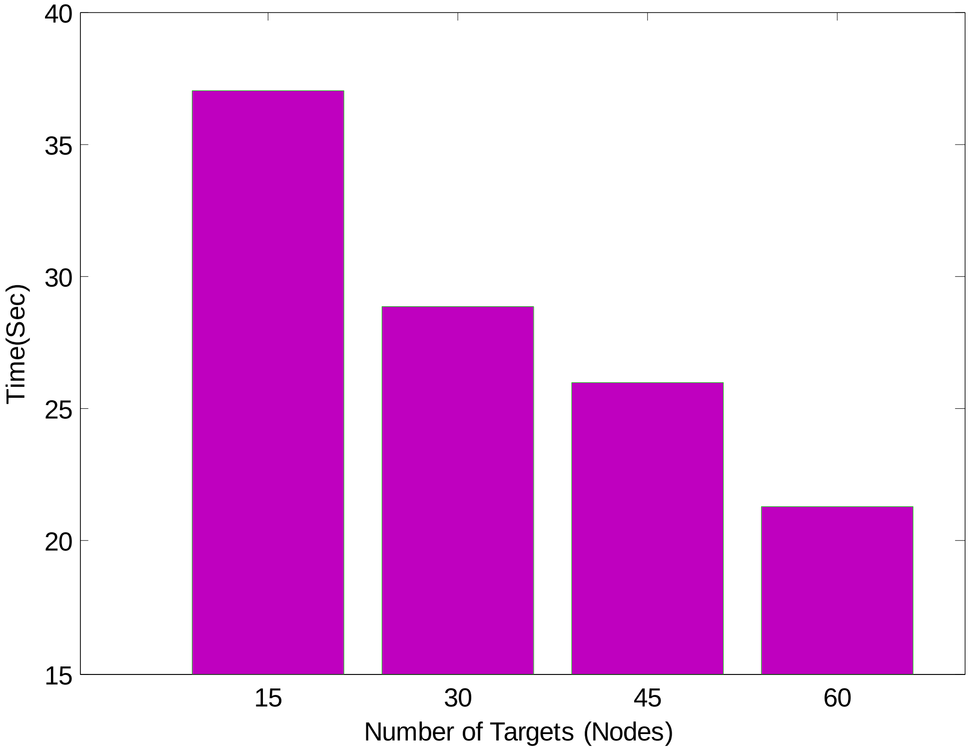


Figure 4.7: Overall Target Tracking Time and Number of Mobile Nodes

From Figure 4.7, it can be observed that the target tracking time decreases as the number of mobile nodes increases. This is expected because, when the number of targets is increased, the joint detection probability increases and the probability of targets falling into the communication range of one another is increased thereby enabling more targets moving into the concentrated regions (clusters). Generally, the faster the target is tracked the better the energy consumption, therefore it is important to track the target into their various location as fast as possible in other reduce energy consumption by individual nodes. From Figure 4.7, it can be observed that, the tracking time can be improved by increasing the number of targets. For example, when the number of targets is 15 the time to efficiently tracked all the targets is 36.558 seconds which is more than the time it takes to tracked 30 targets, 45 targets and 60 targets which are 28.65 seconds, 26.321seconds and 23.036 seconds respectively. Therefore, the time taken to track the 30, 45 and 60 targets are -21.63%, -28.003% and -36.99% less than the time taking to track the 15 targets respectively. This is an indication of energy efficiency. One can significantly increase the tracking time by increasing the number of targets (Fishes or mobile nodes) in the coverage area (Swarm) but, this will cause a significant increase in signal interference, communication consumption and computational complexity. The best way is to increase the number of targets which can achieve the effect of reducing energy (by reducing the overall tracking time) and not compromising the signal interference and communication consumption, computational complexity and network coverage efficiency.

4.7 Validation

In order to validate the proposed wireless sensor network model, this research work employed the work of**Yiyue *et al.*, (2012).**It should be observed from Figure 4.8 that, the plot shows the super imposed response of the proposed model and the model presented in **Yiyue *et al.*, (2012)**.

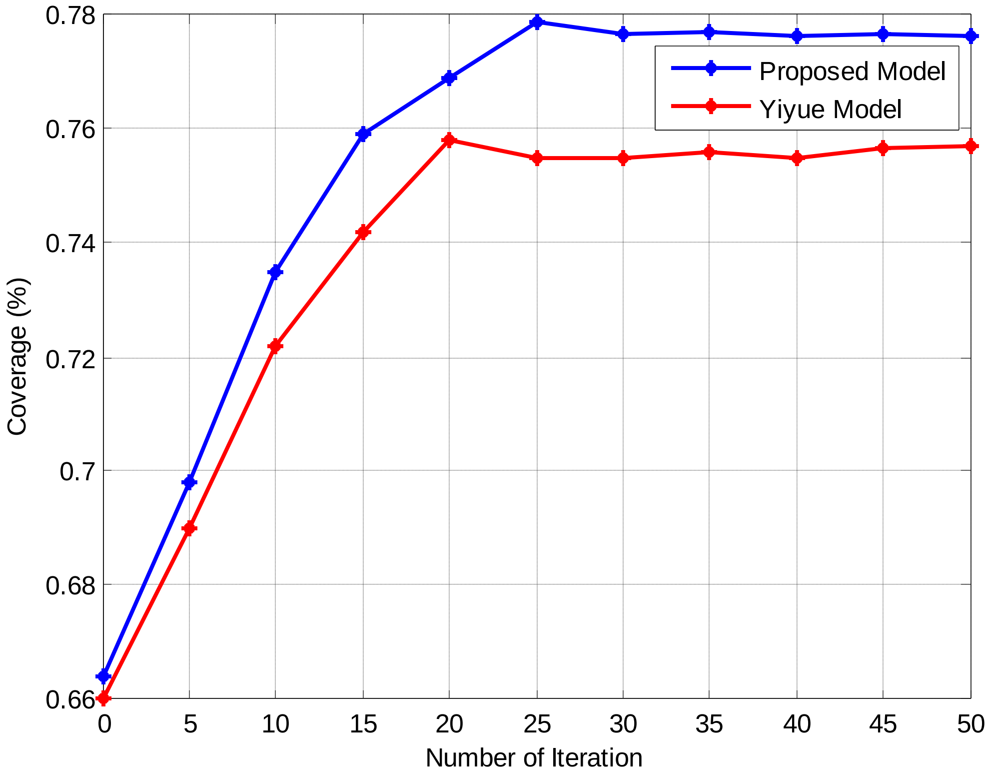


Figure 4.8: Validation of the proposed model

To establish basis for validation, the simulation was done for 50 iteration in interval of 5 iteration. Result shows that, the 77.80% maximum coverage obtained by the proposed model which occurs at 25 iteration is much better when compared with the 74.80% percent obtained by the model proposed in **Yiyue *et al.*, (2012)**atthe same value of iteration.However, the maximum coverage 75.80% obtained by the **Yiyue *et al.*, (2012)**model which occur at 20 iteration is still much lower than the 76.90% obtained by the proposed model at the same value of iteration. This shows the efficiency and validity of the method proposed in this research.

Various performance metric such as; Network coverage and mobile nodes, network coverage and iteration and the effect of various attenuation factor were used to evaluate the performance of the proposed AFSA based WSN model. Simulation results show that the proposed method is valid and can successfully improve the scalability of the WSN.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 Summary

This research has proposed the development of an Artificial Fish Swarm Algorithm based energy efficient target tracking scheme for Wireless Sensor Networks. The following findings were recorded.

i) It was observed that network coverage has direct relationship with the number of network nodes.

ii) It was observed that the network coverage changes with change in iteration.

iii) It was observed that the target tracking time decreases as the number of mobile nodes increases.

iv) It was observed that to reduce energy consumption, the tracking time can be improved y increasing the number of targets.

v) The time taken to track the 30, 45 and 60 targets are -21.63%, -28.003% and -36.99% less than the time taken to track the 15 targets respectively.

vi) To establish basis for validation, the simulation was done for 50 iterations in interval of 5 iteration.

vii) Result shows that the 77.80% maximum coverage obtained by the proposed model which occurs at 25 iteration is better when compared with the 74.80% obtained by the model proposed by Yiyue *et al* (2012) with the same value of iteration.

viii) The maximum coverage 75.80% obtained by the Yiyue *etal* (2012) model which occur at 20 iteration is still much lower than the 76.90% obtained by the proposed model at the same value of iteration.

This shows the efficiency and the validity of the method proposed in this research.

5.2 Conclusion

The research presented an optimal deployment of sensor nodes using an artificial fish swarm optimization algorithm. The positions of network nodes were randomly initialized and the AFSA was used to detect event (based on detection probability) by simulating the preying, swarming and chasing behaviours of fish. The proposed technique was modelled using the communication/control toolbox of Matlab R2013b.Simulation result showed that the network coverage changed with change in iteration. The relationship between network coverage and number of mobile nodes also showed that network coverage increased with increase in mobile nodes. The targets were successfully tracked based on their visual positions. In order to efficiently track the targets while minimizing energy consumption, a trade-off was made between the number of nodes and time of consumption. The target tracking time decreases as the number of mobile nodes increases, this was achieved by increasing the number of targets which can achieve the effect of reducing energy (by reducing overall tracking time).Validation showed that the proposed method is valid as it outperformed the approach presented in Yiyue *et al* (2012).

5.3 Significant Contributions

A lot of research work has been done on improving the energy efficiency in Target Tracking in Wireless Sensor Networks. The significant contributions of this research work are as follows:

i) Development of the network coverage optimal deployment of WSN based on Artificial Fish Swarm optimization Algorithm.

ii) Development of target tracking scheme for WSN considering energy efficiency using AFSA.

iii) Maximum coverage of 77.80% obtained by the proposed model at 25 iteration is better than 74.80% obtained by Yiyue *et al* (2012).

iv) At 20 iteration, the maximum coverage of 75.80% obtained by Yiyue *et al* (2012) model is much lower than the 76.90% obtained by the proposed model.

5.4 Recommendation for Further Work

The following possible further works are recommended for consideration for future research work.

i. Other swarm intelligent algorithm (PSO, BFA, ABC etc.) can be considered as a candidate algorithm to AFSA.

ii. Sensor node deployment at the protocol and application level can be considered.

iii. Different sizes of nodes and different network coverage configuration can be considered.

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AppendixA

m-File of AFSA

```
function AFA
% N is the number of the of artificial Fishes
% D is the dimension of the problem to be optimize
% visual is the visual distance between the artificial fishes
% Zig is the crowd factor (Zigma)
% try_num is the number of trials
% fitness is the objective function to be optimize
% pop(...) represent artificial fish population.
% Initialize the parameters specified by the paper.
%*********************************************
clear all
clc
N=input('Please how many Number of Artificial Fish(N) do you want?:  ');
clc
D=input('What Dimension (D) do you want for each Artificial Fish?:  ');
clc
visual=input('What should be the Visual Distance of the Artificial fishes?:  ');
clc
step=input('Please select the step size of the artificial Fish.:  ');
clc
zig=input('Please enter the Crowd Factor of the Artificial Fish.:  ');
clc
try_num=input('Please enter the number of trials an Artificial fish: ');
clc
fitness=input(‘Select fitness function for WSN deployment’);
clc
FISHS=input('PLEASE ENTER THE INITIAL FISH MATRIX OR \nPRESS ZERO (0)FOR
MATLAB TO CREATE THEM\nFISH:= ');
clc
Itr = input('PLEASE ENTER THE NUMBER OF ITERATIONS: ');
global Xmin Xcentre population
% Generate the artificial fishes which is the same as the Food
% concenteration
tic
if FISHS==0
pop=rand(N,D);
pop=sort(pop);
else
   pop=FISHS;
end
popi=pop;%Initial positions of the AF and start with preying conditions
fitpopi=objfunc(fitness,popi);
```

```
for i=1:N
Try=0;
Itr_max=Itr;
iteration = 0;

while Try<try_num
    iteration = iteration+1;
    Try=Try+1;
    popj(i,(1:D))=popi(i,(1:D))+rand*visual;%randomly selected position
    fitpopj(i,1)=objfunc(fitness,popj(i,(1:D)));
    if fitpopj(i,1)<fitpopi(i,1)
        %Execute preying
    popi(i,(1:D))=popi(i,(1:D))+rand*step*(popj(i,(1:D))-
popi(i,(1:D)))/sum((abs(popj(i,(1:D)).^2-popi(i,(1:D)).^2)).^0.5);
    Try=try_num;
    end
visual=ceil(visual*(Itr_max-iteration)/Itr_max);
step=ceil(step*(Itr_max-iteration)/Itr_max);
try_num=ceil(try_num*(Itr_max-iteration)/Itr_max);

end
if fitpopj(i,1)>fitpopi(i,1)
popi(i,(1:D))=popi(i,(1:D))+rand*step;%Execute if preying fails
end
end
%start Swarming
popii=pop;
fitpopii=objfunc(fitness,popii);
popk=popii+rand*visual;% represent next positions of AF.
for hh=1:N
for h=1:N
    Xcentre=zeros(1,D);
    nf=0;
    if sum(abs(popk(h,:).^2-popii(h,:).^2).^0.5)<=visual %Conditions for  number of fellows btw
visual distance
        nf=nf+1;
        B=popk(h,:);
        Xcentre=Xcentre+B;
    end
end
Xcentre=Xcentre/nf;
Ycentre=objfunc(fitness,Xcentre);
if nf*Ycentre<zig*fitpopii(hh)
    if Ycentre<fitpopii(hh)
        popii(hh,:)=popii(hh,:)+rand*step*(Xcentre-popii(hh,:))/sum((abs(Xcentre.^2-
popii(hh,:).^2)).^0.5);%Uncrowded area
```

```
    else
clear i;
for i=1:N
Try=0;
Itr_max=Itr;
iteration=0;
while Try<try_num
    iteration = iteration+1;
    Try=Try+1;
    popk(i,(1:D))=popii(i,(1:D))+rand*visual;
    fitpopk(i,1)=objfunc(fitness,popk(i,(1:D)));
    if fitpopk(i,1)<fitpopii(i,1)
    popii(i,(1:D))=popii(i,(1:D))+rand*step*(popk(i,(1:D))-
popii(i,(1:D)))/sum((abs(popk(i,(1:D)).^2-popii(i,(1:D)).^2)).^0.5);%Execute Swarming
    Try=try_num;
    end
    visual=ceil(visual*(Itr_max-iteration)/Itr_max);
    step=ceil(step*(Itr_max-iteration)/Itr_max);
    try_num=ceil(try_num*(Itr_max-iteration)/Itr_max);
end
if fitpopk(i,1)>fitpopii(i,1)
popii(i,(1:D))=popii(i,(1:D))+rand*step;
end
end
    end
end
end

%Start Chasing
popiii=pop;
fitpopiii=objfunc(fitness,popii);
popl=popiii+rand*visual;
clear i hh h
for hh=1:N
for h=1:N
    Xmin=[];
    nf=0;
    if  sum(abs(popl(h,:).^2-popiii(hh,:).^2).^0.5)<=visual
        nf=nf+1;
        Xmin=[Xmin;popl(h,:)];
    end
end
clear h;
if nf~=0
for h=1:nf-1
    if  sum(abs(popl(h+1,:).^2-popiii(h+1,:).^2).^0.5)<sum((abs(popl(h,:).^2-popiii(h,:).^2)).^0.5)
```

```
        Xmin=Xmin(h+1,:);
    else
         Xmin=Xmin(h,:); %represent the best artificial fish  individual withing visual distance.
    end
end
end
Ymin=objfunc(fitness,Xmin);
if nf*Ymin<zig*fitpopiii(hh)
    if Ymin<fitpopiii(hh)
        popiii(hh,:)=popiii(hh,:)+rand*step*(Xmin-popiii(hh,:))/sum((abs(Xmin.^2-
popiii(hh,:).^2)).^0.5);
    else
clear i;
for i=1:N
Try=0;
Itr_max=Itr;
iteration=0;
while Try<try_num
    iteration=iteration+1;
    Try=Try+1;
    popl(i,(1:D))=popiii(i,(1:D))+rand*visual;
    fitpopl(i,1)=objfunc(fitness,popl(i,(1:D)));
    if fitpopl(i,1)<fitpopiii(i,1)
    popiii(i,(1:D))=popiii(i,(1:D))+rand*step*(popl(i,(1:D))-
popiii(i,(1:D)))/sum((abs(popl(i,(1:D)).^2-popiii(i,(1:D)).^2)).^0.5);
    Try=try_num;
    end
    visual=ceil(visual*(Itr_max-iteration)/Itr_max);
    step=ceil(step*(Itr_max-iteration)/Itr_max);
    try_num=ceil(try_num*(Itr_max-iteration)/Itr_max);
end
if fitpopl(i,1)>fitpopiii(i,1)
popiii(i,(1:D))=popiii(i,(1:D))+rand*step;
end
end
    end
end
end
%Determing which behavior yield the best solution
population=[];
for Fish=1:N
    for property=1:3
        if property==1
             Best=popi(Fish,:);
        end
             if property==2
```

```
                if objfunc(fitness,Best)>objfunc(fitness,popii(Fish,:))
                    Best=popii(Fish,:);
                end
            end
            if property==3
                if objfunc(fitness,Best)>objfunc(fitness,popiii(Fish,:))
                    Best=popiii(Fish,:);
                end
            end
    end
    population=[population;Best];
end
fitpop=objfunc(fitness,population);
% CM=fitpop
% x=1:60;
plot(fitpop)
grid on
BEST_FITNESS=min(fitpop);
disp('@Author: ')
disp('!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!')
disp('!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!')
disp('NEW ARTIFICIAL FISH ARE HATCHED')
disp('PRESS ANY KEY IF YOU ARE READY FOR THE CHILDREN......')
pause
disp('.....................   ')
disp('.............................   ')
disp('.................................   ')
disp('....................................   ')
disp('INITIAL POPULATION')
disp(pop)
disp('FINAL POPULATION')
disp(population)
BEST_FITNESS
toc
% load laughter
% sound(y,Fs)
% switch fitness
%     case (1)
% end
```

AppendixB

m_File for the target tracking

```
%Target Tracking based on fish swarm algorithm.
%Nodes are tracked in four different location
%Each Nodes location can tracked based on the distances apart.
%Sixty Nodes is Choosing to ensure efficient tracking and Avoid the no see
%the forest for the three role, while maintaining a trade-off efficiency and energy %consumption
% ============================================================== %
Functiontrack_target
clc
clear all
close all
% n=number of nodes
n=input('Please Enter the number of Nodes to be tracked: ');
Try=input('Please Enter the number of Iteration: ');
helptrack_AFSA.m
rand('state',0);  % Reset the random generator
funstr=input(‘Please Provide the Target Tracking Function’);
% Converting to an inline function
f=vectorize(inline(funstr));
% range=[xminxmaxyminymax];
Range=input (‘Please Provide the Range’);
% --------------------------------------------------
Alpha=input(‘Provide Alpha’);      % Randomness 0--1 (highly random)
gamma=input(‘Provide Gamma’);      % Absorption coefficient
delta=input(‘Provide Detlta’);     % Randomness
% --------------------------------------------------
% Grid values are used for display only
Ngrid=100;
dx=(range(2)-range(1))/Ngrid;
dy=(range(4)-range(3))/Ngrid;
[x,y]=meshgrid(range(1):dx:range(2),...
range(3):dy:range(4));
z=f(x,y);
% Display the shape of the objective function
% figure(1);
% surfc(x,y,z);
% --------------------------------------------------
% generating the initial locations of n mobile nodes
[xn,yn,Lightn]=node_init(n,range);
% Display the paths of nodes in a figure with
% contours of the function to be optimized
figure(2);
fori=1:Try
```

```
contour(x,y,z,50);
hold on;
% Evaluate new Positions
zn=f(xn,yn);
[Lightn,Index]=sort(zn);
xn=xn(Index);
yn=yn(Index);
xo=xn;
yo=yn;
Lighto=Lightn;
% Trace the paths of random NODES
plot(xn,yn,'or','markersize',20,'markerfacecolor','g');
xlabel('X-coodinate')
ylabel('Y-coodinate')
[xn,yn]=node_move(xn,yn,Lightn,xo,yo,Lighto,alpha,gamma,range);
drawnow;
% Use "hold on" to show the paths of NODES
hold off;
alpha=newalpha(alpha,delta);
end   %%%%% end of iterations
best(:,1)=xo';
best(:,2)=yo';
best(:,3)=Lighto';
function [xn,yn,Lightn]=node_init(n,range)
xrange=range(2)-range(1);
yrange=range(4)-range(3);
xn=rand(1,n)*xrange+range(1);
yn=rand(1,n)*yrange+range(3);
Lightn=zeros(size(yn));
function [xn,yn]=node_move(xn,yn,Lightn,xo,yo,...
Lighto,alpha,gamma,range)
ni=size(yn,2); nj=size(yo,2);
fori=1:ni
for j=1:nj,
r=sqrt((xn(i)-xo(j))^2+(yn(i)-yo(j))^2);
ifLightn(i)<Lighto(j)
beta0=1;
beta=beta0*exp(-gamma*r.^2);
xn(i)=xn(i).*(1-beta)+xo(j).*beta+alpha.*(rand-0.5);
yn(i)=yn(i).*(1-beta)+yo(j).*beta+alpha.*(rand-0.5);
end
end % end for j
end % end for i
[xn,yn]=findrange(xn,yn,range);

% Reduce the randomness during iterations
```

```
function alpha=newalpha(alpha,delta)
alpha=alpha*delta;

% Make sure the Nodes are within the range
function [xn,yn]=findrange(xn,yn,range)
fori=1:length(yn)
ifxn(i)<=range(1)
xn(i)=range(1);
end
ifxn(i)>=range(2)
xn(i)=range(2);
end
ifyn(i)<=range(3)
yn(i)=range(3);
end
ifyn(i)>=range(4)
yn(i)=range(4);
end
end
end
%  ============== end ======================================
disp('@Aurthos:')
disp('Lawal Samira Abdulhamid')
disp('Dr.A.D. Usman')
disp('Dr. S. Garba')
disp('Professor M.B. Mua'zu')
```

AppendixC

m_File for the Response considering attenuation

```
clc
clear all
close all
iteration=a:x:b %provide the number of iteration;
G=input(‘Provide the values: ’);
R=input(‘Provide the values: ’);
B=input(‘Provide the values: ’);
M=input(‘Provide the values: ’);
%plot the first respose
figure(1)
plot(iteration,B)
hold on
%plot the second response
plot(iteration,R,'r')
hold on
%plot the third response
plot(iteration,G,'g')
hold on
%plot the fourth response
plot(iteration,M,'y')
%Include Legend and Gride
grid on
legend('attenuation = 0.90','attenuation = 0.85','attenuation = 0.80','attenuation = 0.75')
```

Appendix D

m_File for the bar chart

```
close all
clear all
clc
figure(2)
%Provide the parameters
Time=input(‘Provide the values: ’);
x=a:x:b;%please provide the values
%Plot the bar chart
a=bar(x,Time,'m')
xlabel('Number of Targets (Nodes)')
ylabel('Time(Sec)');
a.LineWidth=10;
a.EdgeColor='red';
```

Appendix E

Table 4.1. Simulation Result for the Relationship between the Network Coverage and Sensor Nodes.

SN:	Network Nodes	Network Coverage
1	5	0.7180
2	10	0.7350
3	15	0.7500
4	20	0.7590
5	25	0.7692
6	30	0.7791
7	35	0.7860
8	40	0.7902
9	45	0.7935
10	50	0.8013
11	55	0.8005
12	60	0.8007

From Table 4.1, it can be observed that, the Network Coverage has direct relationship with the number of network nodes.

Appendix F

Table 4.2.Relationship between Network Coverage and Number of Iterations

SN:	Network Coverage	Number of Iteration
1	0.6640	5
2	0.6980	10
3	0.7350	15
4	0.7690	20
5	0.7787	25
6	0.7690	30
7	0.7740	35
8	0.7730	40
9	0.7740	45
10	0.7722	50
11	0.7742	55
12	0.7742	60

The result shown in Table 4.2 indicates that, as the number of iteration increases the network coverage increases up until after 25 iterations

Appendix G

Table 4.3.Relationship between Network Coverage and Number of Iterations for Different Attenuation

	Network Coverage				
SN:	α = 0.75	α = 0.80	α = 0.85	α = 0.90	No. of Iterations
1	0.6779	0.6825	0.6830	0.6850	5
2	0.7046	0.7079	0.7109	0.7280	10
3	0.7053	0.7099	0.7190	0.7520	15
4	0.7058	0.7060	0.7260	0.7500	20
5	0.7054	0.7052	0.7249	0.7600	25
6	0.7053	0.7054	0.7263	0.7570	30
7	0.7055	0.7057	0.7265	0.7647	35
8	0.7051	0.7057	0.7269	0.7715	40
9	0.7052	0.7057	0.7266	0.7690	45
10	0.70510	0.7057	0.7266	0.7709	50
11	0.7051	0.7057	0.7266	0.7702	55
12	0.7051	0.7057	0.7266	0.7705	60

The result shown in Table 4.3 indicates that, as the number of iterations increases, the network coverage also increases.