M.TECH THESIS REPORT

RANGE BASED NODE LOCALIZATION IN WIRELESS SENSOR NETWORK USING BBO AND PSO

Submitted in partial fulfillment of the requirements for the degree of Master of Technology in Electronics & Communication Engineering by

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CERTIFICATE

I, Shivangna, hereby declare that the work being presented in this thesis on RANGE BASED WIRELESS SENSOR NODE LOCALIZATION is an authentic record of my own work carried out by me during my course under the supervision of Dr. Satvir Singh. This is submitted in the Department of ECE at Shaheed Bhagat Singh State Technical Campus, Ferozepur (affiliated to Punjab Technical University, Jalandhar) as partial fulfillment of requirements for award of the degree of Masters of Technology in Electronics and Communication Engineering.

Shivangna (1169063)

To the best of my knowledge, this thesis has not been submitted to Punjab Technical University, Jalandhar or to any other university or institute for award of any degree or diploma. It is, further, understood that by this certificate the undersigned does not endorse or approve any statement made, opinion expressed or conclusion drawn there in, however, approve the thesis only for the purpose for which it is submitted.

Dr. Satvir Singh [Supervisor]

The M.Tech Viva-Voce Examination of Shivangna is held at Department of ECE, SBS State Technical Campus, Ferozepur on ....

Name: ....
External Examiner

Sanjeev Dewra
Head, Department of ECE

Dedicated to

My Guide and Family

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Shivangna

THESIS OUTCOMES

International/National Journal Publications/Submissions

1. S. Singh, Shivangna and S. Tayal, "Analysis of Different Ranges For Wireless Sensor Node Localization using PSO and BBO and its variants," Vol. 63, No. 22, February 2013, pp. 31-37, published in Foundation of Computer Science, New York, USA.

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International/National Conference Publications/Submissions

1. S. Singh, Shivangna and E. Mittal, "Range Based Wireless Sensor Node Localization using PSO and BBO and its variants," accepted in CSNT (2013) IEEE International Conference.

2. S. Singh, Shivangna, E. Mittal, "Performance of PSO with Different Ranges for Wireless Sensor Node Localization," published in UGC Sponsored National Conference in technical collaboration with IEEE-EMBS/IMS.

ABSTRACT

In Wireless Sensor Networks (WSN), accurate location of target node is highly desirable as it has strong impact on overall performance of the network. This thesis presents investigations on performance of Particle Swarm Optimization (PSO), Biogeography Based Optimization (BBO) and migration variants of BBO for localization of randomly deployed sensor nodes having different transreception ranges. Wireless sensor nodes are equipped with low power sensors with wireless communication capability. They can be deployed in a physical environment to sense parameters temperature, light and moisture, etc. The data gathered by these nodes are processed to get relevant information about environment at the sink. Characteristics of WSN like self organizing and fault tolerance make them promising for a number of military, civilian and industrial applications, e.g., weather, snow levels at hills, industrial monitoring and automation, etc. Many of the applications that are proposed for WSN requires knowledge for origin of sensing information which gives rise to problem of localization. Localization is most active research area in WSN and it usually refers to the process of determining the positions of all nodes in the network. Determination of node coordinates in WSN can be formulated as complex optimization problem. Node localization taxonomy consists of phases like range-based, range-free, anchor-based, anchor-free algorithm. The process of localization is to determine actual position of the nodes with minimum error.

PSO is a robust stochastic optimization technique inspired from learning and imitating behaviour of natural swarm, like birds, and fish, etc. It was developed by James Kennedy (Social psychologist) and Russell Eberhart (Electrical Engineer) in 1995 as an extension to Hollywood animations of a bird flock for some film. It uses a number of particles that constitute a swarm moving around in a search space looking for the best fit position / solution.

BBO is population based stochastic optimization technique inspired from science of biogeography, i.e., the study of distribution of biological species, over space and time. BBO involves two inherent activities: (a) the exploitation of available solution features (species) is made to happen using process of migration among various potential solutions (habitats), (b) the exploration of new solution features occur due to mutation operator. To minimize average localization error in WSN, PSO, BBO and migration variants of BBO are experimented and investigated for faster convergence and to determine actual position. QT Creator is used to create BBO algorithm, PSO algorithm in C++ programming environment.

BBO variants can be classified into two categories, i.e., Migration variants and Mutation variants. Till date, PSO and BBO have reported for localization in Wireless Sensor Network for comparison with transmitting range = 25 units on a network area of 100 * 100 square units. However, in this thesis three BBO migration variants (a) Blended BBO (b) Enhanced BBO (c) Immigration Refusal along with PSO have been investigated for localization of 50 sensors (targets) with the help of 10 and 15 anchor nodes having radial transmitting range of 15, 20 and 25 units. PSO and migration variants of BBO were resulted in better localization consuming less computational time.

During simulation, 25 trials for each stochastic algorithm were conducted with different noise levels i.e., 2 and 5. Average of all 25 evolutionary runs are presented for fair comparative investigations or convergence performance of PSO, BBO and migration variants of BBO. C++ programming platform is used for coding of PSO, BBO and migration variants of BBO. From simulation results, it can be observed that Blended BBO determines accurate coordinates as compared to other EAs. Nodes having wider range are localized better as compared to network having sensor nodes with less transmitting range that is reported in [Satvir Singh, 2013b], [Singh et al., 2013], [Satvir Singh, 2013a]. With more number of anchor nodes in same area more nodes gets localized with less average localization error.

This thesis is outlined as follows: Chapter 1 is depicted to introduction of thesis as whole that covers introduction to research topic, motivation, objectives and methodology. Study of literature survey in Wireless Sensor Network and Evolutionary Algorithms are represented in Chapter 2. In Chapter 3, WSN localization and taxonomy are discussed to have some background knowledge about WSN. In Chapter 4 philosophy of BBO and migration variants of BBO are discussed that are experimented for minimizing average localization error. In Chapter 5, PSO algorithm is discussed and it is experimented for minimizing average localization error. Chapter 6, discusses the implementation of localization algorithms based

BBO and PSO in C++ programming environment using QT Creator. Simulation results are presented, in chapter 7, along with respective discuss. Lastly, conclusion and future scope have been discussed in chapter 8.

Place: Ferozepur SHIVANGNA [1169063]

Date: July 15, 2013

ABBREVIATIONS

Abbreviations	Description
AOA	Angle of arrival
BBO	Biogeographical Based Optimization
DARPA	Defence Advanced Research Project Agency
DSN	Distributed Sensor Networks
EA	Evolutionary Algorithm
EBBO	Enhanced Biogeography Based optimization
GA	Genetic Algorithm
gbest	Global Best Particle
GPS	Global Positioning System
GUI	Graphical User Interface
HSI	Habitat Suitability Index
pbest	Previous Best Particle
PSO	Particle Swarm Optimization
RSSI	Received Signal Strength Indicator
RTT	Round Trip Time
SIV	Suitability Index Variable
TDOA	Time-Difference of arrival
TOA	Time of arrival
WSN	Wireless Sensor Networks

NOTATIONS

Symbols	Description
D_{t_i}	Actual Distance
$\hat{D}_{t_i}$	Estimated Distance
x_t	x coordinate of Target node
x_i	x coordinate of Anchor node
y_t	y coordinate of Target node
y_i	y coordinate of Anchor node
M	Number of Anchor nodes within transmission radius of the target node
P_n	Percentage noise in distance measurement
N_l	Localizable nodes
E_l	Total localization error
p_g	Best particle in overall swarm
w	Inertia weight
V_{max}	Particles movement with maximum velocity
H	String of BBO
μ_k	Emigration rate
λ_k	Immigration rate
N	Unknown nodes
ψ_1	Cognitive Learning Parameter
ψ_2	Social Learning Parameter

χ	Constriction Factor
X_i	i-th particle location in the swarm
V_i	i-th particle velocity in the swarm
r_1 & r_2	Random numbers uniformly distributed in the range [0,1]
p_{id}^n	Past best particle location in n-th iteration
p_{gd}^n	Global best particle location in n-th iteration
v_{id}^n	Current velocity
α	Random number between [0, 1]

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Wireless Sensors Networks (WSNs) are the networks of distributed autonomous nodes that can sense their environment cooperatively. WSN are networks that consists of sensors which are distributed in an ad hoc manner. Wireless sensor nodes are equipped with low power sensors with wireless communication capability. They can be deployed in a physical environment to sense parameters temperature, light and moisture, etc. The data gathered on these nodes are processed to get relevant information about environment at the sink. WSN consists of protocols and algorithms with self-organizing capabilities. Every node consists of Sensing Module, Receiving and Transmission Module. Wireless sensor networks mainly use broadcast communication while ad hoc networks use point-to-point communication. Range -based localization schemes deploy complex and dedicated measurements mechanism to infer range information (in terms of distance of angle estimates) for calculating location of target nodes.

PSO is a robust stochastic optimization technique based on the movement and intelligence of swarms. PSO applies the concept of social interaction to problem solving. It was developed in 1995 by James Kennedy (social-psychologist) and Russell Eberhart (electrical engineer). It uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution.

BBO was studied by Alfred Wallace and Charles Darwin mainly as descriptive study. In 1967, the work carried out by MacAurthur and Wilson changed this view point and proposed a mathematical model for biogeography and made it feasible to predict number of species in a habitat.

1.1.1 Wireless Sensor Networks

Wireless sensor networks are used in diverse applications such as environment and habitat monitoring, structural health monitoring, health care, home automation, and traffic surveilance. In many circumstances, it is useful or even necessary for a node in WSN to be aware of its location in the physical world. For example tracking and event detection functions are not particularly useful if WSN cannot provide any information where an event has happened. To do so, usually, reporting nodes location has to be known. Manually configuring location information into each node during deployment is not an option. Similarly, equipping every node with a GPS receiver fails because of cost and deployment limitations (GPS does not work as indoor).

1.1.2 Localization Problem

Localization is of most active research area in WSN. Localization usually refers to process of determining the positions of one or more nodes in large network. Many of the applications proposed for WSN require knowledge of origin of sensing information which gives rise to problem of localization.

1.1.3 Particle Swarm Optimization

PSO is a robust stochastic optimization technique inspired from learning and initiating behaviour of natural swarm, like birds, and fish, etc. It uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution. Each particle keeps track of its coordinates in the solution space which are associated with the best solution (fitness) that has achieved so far by that particle.

1.1.4 Biogeography Based Optimization

BBO is a population based stochastic optimization technique inspired from science of biogeography, i.e., the study of distribution of biological species, over space and time. Basically biogeography was studied by Alfred Wallace and Charles Darwin mainly as descriptive study. In 1967, the work carried out by MacAurthur and Wilson changed this view point and proposed a mathematical model for biogeography and made it feasible to predict number of species in a habitat. BBO variants can be classified into two categories, i.e., migration variants and mutation variants. Migration may lead to same types of habitats because of copying SIVs or features from habitats having high HSI to low HSI habitat. To reduce number of same types of habitats and make BBO convergence faster, migration variants are introduced. BBO has three migration variants that are as follows

1. Blended Migration
2. Immigration Refusal
3. Enhanced Biogeography-Based Optimization

1.2 Motivation

WSN localization is treated as a multidimensional optimization problems and addressed through population-based techniques recently. PSO, BBO and its migration variants algorithms are used for determining coordinates of nodes in a WSN in a distributed and iterative fashion. Distributed localization has advantage of reduced number of transmissions to the base station, which help the nodes to conserve their energy, which is a serious concern in most WSN applications. This was implemented in [Kulkarni et al., 2009]. They use MATLAB as programming platform. PSO, BBO and its migration variants can be used in localization method in order to compare their performances on basis of minimum average localization error.

PSO have better accuracy and fast convergence in highly noise environment. It determines the accurate nodes quickly. The choice between two algorithms depends upon the trade-off between accuracy and fast convergence. Through intensive simulations, emphasis as iteration progress, more nodes get settled and require few anchors to find the coordinates of the target nodes. This was implemented in [Kumar et al., 2012]. It may be implemented for range-free localization and a comparison can be made for energy awareness. A hybrid stochastic algorithm may be proposed to achieve both accuracy and faster convergence.

1.3 Objectives

The primary objectives of this research work are summarized as follows:

1. To study Wireless sensor networks in localization, in details, in order to explore the scope of simplification of design methodology.

2. To study PSO algorithm, BBO and its migration variants algorithms in details, and investigate for their further improved performance.
3. How to use PSO algorithm, BBO and its migration variants algorithms to localize sensor nodes in wireless networks.

1.4 Methodology

For the Range-based localization in Wireless Sensor Networks using stochastic algorithms are as follows:

1. How to utilize EAs with WSN.
2. Exist an unknown node which has at least 3 anchor nodes on its coverage area or range (given) to be localized.
3. Estimate distance to reference node.
4. Calculate the average of those anchor nodes and consider that position to be estimated target node.
5. Randomly deploy few nodes around that estimated position.
6. Calculate position of selected unknown node by calculating the error minimization function by applying any stochastic approach like PSO, BBO and its migration variants.
7. How to use QT Creator as a programming platform to make accurate and fast processing performance and to compare the performances of other EAs in Wireless Sensor Networks to get the minimum average localization error.

1.5 Contributions

The main contributions of this report are:

1. To study WSN localization for design issues.
2. To create PSO and BBO algorithms on QT Creator C++.
3. To explore various migration variants to minimize localization error.

1.6 Thesis Outline

Chapter 2 starts with literature survey in which historical development in localization using EA's in WSN reported till date.

Chapter 3 is devoted to WSN localization and its phases are discussed to have some background knowledge about WSN.

Chapter 4 discusses the philosophy of biogeography and inspired algorithms with different migration variants and their algorithms.

Chapter 5 discusses philosophy of Particle Swarm Optimization and PSO algorithm.

Chapter 6 discusses simulation platform of Qt Creator and flow diagram of localization process using PSO, BBO and its migration variants.

Chapter 7 is dedicated to simulation results of performance of PSO and BBO and its migration variants to minimize localization error. Best results in tabulated form is also presented in this chapter.

Lastly, conclusion and future scope are discussed in Chapter 8.

CHAPTER 2

LITERATURE SURVEY

2.1 Introduction

WSNs are different from traditional wireless ad-hoc networks due to their unique features and application requirements. Important features of WSNs are given below:

1. The number of sensor nodes in a WSN is several orders higher than the nodes in ad hoc networks.
2. Typical WSNs are densely deployed and prone to failures.
3. Since new sensor nodes can join the network and some of the nodes may die out, WSNs have got dynamic network topology even when the nodes are stationary.
4. Sensor nodes are very much limited in their power, computation, and memory resources so that protocols developed for such networks should be highly scalable and energy efficient.
5. Sensor nodes may not have a unique global identification due to the large number of sensors and the overhead associated with it.
6. Sensor networks are deployed with specific sensing applications unlike the ad-hoc networks which are mostly constructed for communication purposes.

2.2 Wireless Sensor Networks

In WSN system numerous radio nodes collaborate to allow communication in the absence of fixed infrastructure. With the flexibility and scalability, WSNs have great potential for a variety of applications including environmental monitoring, health care, target tracking, and military surveillance. Most of these applications require the knowledge about the location of each node because data stream of node presents the state or context in the location. Localization has been made an essential demand to realize location-based applications and methods in WSNs. GPS may be straightforward solution to the localization problem. However, GPS is unavailable in indoor environments and even in outdoor environments where buildings block the satellite signal. In addition, GPS is inadequate for scalable and resources-limited networks since the leads to increase in installation costs and reduction in lifetime.

WSN are particularly interesting in hazardous or remote environments or when a large number of sensor nodes have to be deployed. The localization issue is important where there is uncertainity about some positioning. If sensor networks is used for monitoring temperature in a building it is likely that we can knowing exact position of each node. On the contrary if sensor network is used for monitoring temperature in remote forest, nodes may be deployed from an aeroplane and precise location of most sensors may be unknown. An effective localization algorithm can then use all available information to compute all positions.

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2.2.1 Design challenges in WSN

The design challenges in WSN are as follows:

1. **Scalability**: Design must be in such a manner that deploying many nodes in network does not affect clustering and routing.
2. **Power Consumption**: Focusing should be on design of power available algorithms for sensor networks.
3. **Short range transmission**: In WSN we should consider short range transmission in order to reduced possibility of eavesdropped.
4. **Hardware Design**: While designing any hardware of sensor network it should be energy efficient.
5. **Security**: Security is very important parameter in sensor networks so it should be high.

2.2.2 Historical Development in Localization

A survey of localization systems of WSNs is available in [Boukerche et al., 2007]. An efficient localization system that extends GPS capabilities to non-GPS nodes in an ad-hoc network as anchors transmit their location information to all nodes in the network is proposed in [Niculescu and Nath, 2001]. Then, each target node estimates its location by performing triangularization. Localization accuracy of node is improved by measuring their distances from their neighbors in [Rabaey and Langendoen, 2002]. The issue of error accumulation is addressed in [Savvides et al., 2002] through Kalman filter based least square estimation in [Di Rocco and Pascucci, 2007; Kalman, 1960] to simultaneously locate the position of all sensor nodes. Node localization problem is addressed using convex optimization based on semi-definite programming. The semi-definite programming approach is further extended to non-convex inequality constraints in [Biswas et al., 2006]. In [Liang et al., 2004], Gradient search technique demonstrates the use of data analysis technique called multidimensional scaling (MDS) for estimating the target node positions. WSN is treated as multidimensional optimization problem and addressed through population based stochastic approaches. In [Gopakumar and Jacob, 2008] centralized location of WSN nodes is proposed by PSO to minimize average localization error. In this approach it provides more accurate localization as compared to simulated annealing algorithm proposed earlier [Kannan et al., 2005]. This approach required few known nodes (anchors) to localize all target nodes. Range Based localization using PSO, BBO and its migration variants are presented in [Satvir Singh, 2013b]. Comparison of two different ranges using PSO and BBO and its migration variants are presented in [Singh et al., 2013], [Satvir Singh, 2013a]. Non-Dominating sorting for BBO is presented in [Singh et al., 2012b]. Multi-objective gain impedance optimization of Yagi-Uda antenna is presented in [Singh et al., 2012a]. Performance of graded emigration in BBO for Yagi-Uda antenna design optimization is presented in Satvir Singh and Shivangna [2013].

Some Genetic Algorithms (GA) based node localization are proposed in [Nan et al., 2007; Yun et al., 2009; Zhang et al., 2008a,b]. Centralized algorithm determines location of target node by estimating their distances from all one hop neighbors. Each target node is localized under imprecise measurement of distances from three or more neighboring anchors nodes or settled nodes. The method proposed in this paper has following advantages over some of the earlier methods:

1. Localization is robust against uncertainty of noise associated with distance measurement.
2. Localization accuracy is better and has fast convergence.
3. In each iteration, one node gets settled and acts as reference node (anchor node) to other unknown nodes in next iteration. Thus, each node gets more references in its

transmission range. This leads to minimization in error due to flip ambiguity, the situation that arises as reference (anchor) nodes are in non-collinear locations.

2.3 Particle swarm optimization

PSO is a robust stochastic optimization technique inspired from learning and imitating behaviour of natural swarm like birds, and fish, etc. PSO applies the concept of social interaction to problem solving. It was developed in 1995 by James Kennedy (social-psychologist) and Russell Eberhart (electrical engineer). It uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution. Each particle keeps track of its coordinates in the solution space which are associated with the best solution (fitness) that has achieved so far by that particle. This value is called personal best, *pbest*. Another best value that is tracked by the PSO is the best value obtained so far by any particle in the neighborhood of that particle. This value is called *gbest*. The basic concept of PSO lies in accelerating each particle toward its *pbest* and the *gbest* locations, with a random weighted acceleration at each time step as shown in Fig. 2.1.

Later on, it was realized that the simulation could be used as an optimizer and resulted in the first simple version of PSO. In PSO, the particles have (1) adaptable velocities that determines their movement in the search space, (2) memory which enable them for remembering the best position in the search space ever visited. The position corresponding to the best fitness is known as past best, *pbest*, and the overall best out of all NP the particles in the population is called global best, *gbest*. Consider that the search space is M-dimensional and i-th particle location in the swarm can be represented by $X_i = [x_{i1}, x_{i2}, ...x_{id}..., x_{iM}]$ and its velocity can be represented by another M-dimensional vector $V_i = [v_{i1}, v_{i2}, ...v_{id}.., v_{iM}]$. Let the best previously visited location position of this particle be denoted by $P_i = [p_{i1}, p_{i2}, ...p_{id}.., p_{iM}]$, whereas, g-th particle, i.e., $P_g = [p_{g1}, p_{g2}, ...p_{gd}.., p_{gM}]$, is globally best particle location. Fig. 2.1 depicts the vector movement of particle element from location x_{id}^n to x_{id}^{n+1} in $(n+1)$-th iteration that is being governed by past best location, p_{id}^n, global best location, p_{gd}^n, and current velocity v_{id}^n. Alternatively, the whole swarm is updated according to the equations (2.1) and (2.2) suggested by [Hu et al., 2004], [del Valle et al., 2008].

$$v_{id}^{n+1} = \chi(wv_{id}^n + \psi_1 r_1(p_{id}^n - x_{id}^n) + \psi_2 r_2(p_{gd}^n - x_{id}^n)) \tag{2.1}$$

$$x_{id}^{m+1} = x_{id}^m + v_{id}^{m+1} \tag{2.2}$$

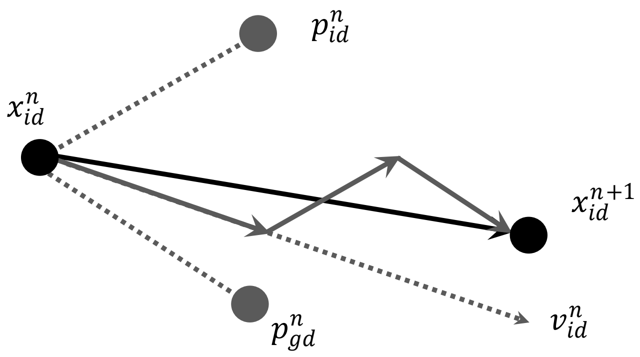

FIGURE 2.1: PSO Characterstics

Here, w is inertia weight, ψ_1 is cognitive learning parameter, ψ_2 is social learning parameter and constriction factor, χ, are strategy parameters of PSO algorithm, while r_1 and r_2 are random numbers uniformly distributed in the range [0,1]. Generally the inertia weight, w, is not kept fixed and is varied as the algorithm progresses. The particle movements is restricted with maximum velocity, $\pm V_{max}$, to avoid jump over the optimal location as per search space requirements.

2.4 BBO and its Variants

BBO is one of the recently developed population based algorithms which has shown impressive performance over other Evolutionary algorithms(EAs). BBO is a population based global optimization technique developed on the basis of science of biogeography, i.e., study of distribution of animals and plants among different habitats over time and space that is shown in Fig. 2.2. The results of BBO are better as compared to other optimization techniques like Particle Swarm Optimization, Genetic algorithms, Ant Colony Optimization and Simulated annealing [Nan et al. [2007], Yun et al. [2009], Zhang et al. [2008b], Zhang et al. [2008a]]. Basically biogeography was studied by Alfred Wallace [Wallace, 1876] and Charles

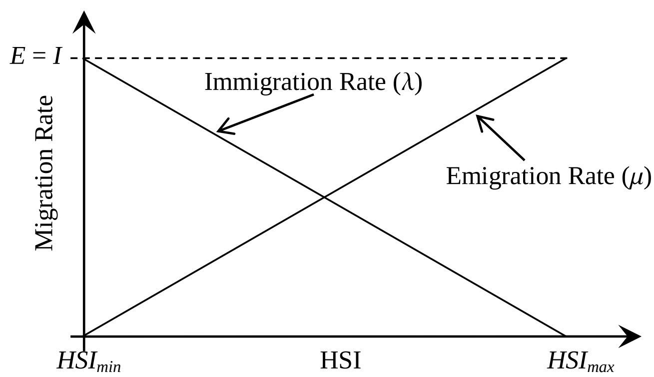

FIGURE 2.2: BBO Charactersitics

Darwin [Darwin and Beer, 1869] mainly as descriptive study. In 1967, the work carried out by MacAurthur and Wilson [MacArthur and Wilson, 2001] changed this view point and proposed a mathematical model for biogeography and made it feasible to predict number of species in a habitat. Localization estimated by BBO is described in [Kumar et al., 2012]. Migration may lead to same types of habitats because of copying SIVs or features from habitats having high HSI to low HSI habitat.

2.4.1 Features of High HSI habitats

Features of high HSI habitats are given as follows:

1. Habitat with high HSI tend to have a large number of species, while those with low HSI have small number of species.
2. Habitats with HSI have low immigration rate because they are already nearly saturated with species.
3. They have high emigrating rate; large number of species emigrate to neighboring habitats
4. A good solution represent a habitat with high HSI, good solutions have more resistance to change than poor solutions

2.4.2 Features of Low HSI habitats

Features of low HSI habitats are given as follows:

1. Habitats with low HSI have high immigration rate and low emigrate rate because of their sparse population.
2. The immigration of new species to low HSI habitats may raise the HSI of the habitat.
3. As HSI is proportional to biological diversity.
4. Poor solution represent a habitat with a low HSI. Poor solutions are more dynamic and accept a lot of new feature from good solutions.

To reduce number of same types of habitats and make BBO convergence faster, migration variants are introduced. BBO has three migration variants that are discussed as follows:-

1. Blended Migration

2. Immigration Refusal
3. Enhanced Biogeography-Based Optimization

2.4.3 Blended Migration

Blended Migration operator is a generalization form of the standard BBO migration operator and inspired by blended crossover in GAs [McTavish and Restrepo, 2008]. In blended migration, a solution feature of solution H_i is not simply replaced by a feature from solution H_j that happened in standard BBO migration operator. Instead, a new solution feature, in blended migration, solution is comprised of 2 components, the migration of a feature from another solution and migration of feature from itself, i.e., $H_i(SIV) \leftarrow \alpha \cdot H_i(SIV) + (1 - \alpha) \cdot H_j(SIV)$ where α is the random number between 0 and 1.

2.4.4 Immigration Refusal

In BBO, if a habitat has high emigration rate, i.e., the probability of emigrating to other habitats is high and the probability of immigration from other habitats is low. Once in a while, a highly fit solution with migrate solution features from a low fit solution to high fit solution. This may degrade the high fitness of the habitats which receives immigrants. If high fitness of solution decreases after receiving the immigrants, then immigrating habitat may refuse the immigrating solution features [Du et al., 2009].

2.4.5 Enhanced Biogeography-Based Optimization

Standard BBO migration operator creates the duplicate solutions which decreases the diversity of algorithm. To prevent the harmful over similarity among the solutions, clear duplicate operator with random mutation is utilized, i.e., EBBO [Pattnaik et al., 2010].

2.5 Conclusion

In literature survey, we conclude that Bio-inspired algorithms i.e., PSO and BBO are for determining coordinates of the unknown nodes of WSN in a distributed and iterative fashion. Distributed localization proposed here has the advantage of reduced number of transmissions to the base stations which helps the nodes to conserve their energy, which is a serious concern in most WSN applications. Further variants of BBO and PSO can also be used in determining unknown nodes in sensor networks. A comparison with PSO and BBO and its migration variants for different ranges and various number of anchors in terms of number of nodes localized, localization accuracy and computational time can be done.

CHAPTER 3

WSN NODE LOCALIZATION

3.1 Introduction to Wireless Sensor Network

Wireless sensors are equipped with low power microscopic sensors with wireless communication capability. They are with small physical size that can be embedded in physical environment. WSN consists of protocols and algorithms with self-organizing capabilities. Every node consists of Sensing Module, Receiving and Transmission Module. Wireless sensor networks mainly use broadcast communication while ad hoc networks use point-to-point communication. It supports powerful service in aggregated form by interacting/collaborating among nodes. Sensor networks are key to gathering the information needed by smart environments whether in buildings, utilities, industrial, home, shipboard, transportation systems automation or elsewhere. In such applications, running wires or cabling is usually impractical. A sensor network is required that is fast and easy to install and maintaining. The study of WSN is challenging in that it requires an enormous breadth of knowledge from an enormous variety of disciplines. WSN have many applications also in military and commercial areas like tracking that is shown in Fig. 3.1

As with many technologies the military has been a driving force behind the development of WSN. For eg in 1978, the defence advanced research project agency (DARPA) organized the distributed sensor networks workshop (DAR 1978), focussing on sensor network research challenges such as networking technologies, signal processing techniques, and distributed algorithms. DARPA also operated the distributed sensor networks (DSN) program in early 1980's which was then followed by the sensor information technology (SensIT) program. In collaboration with the rockwell science centre, the university of california at Los Angeles

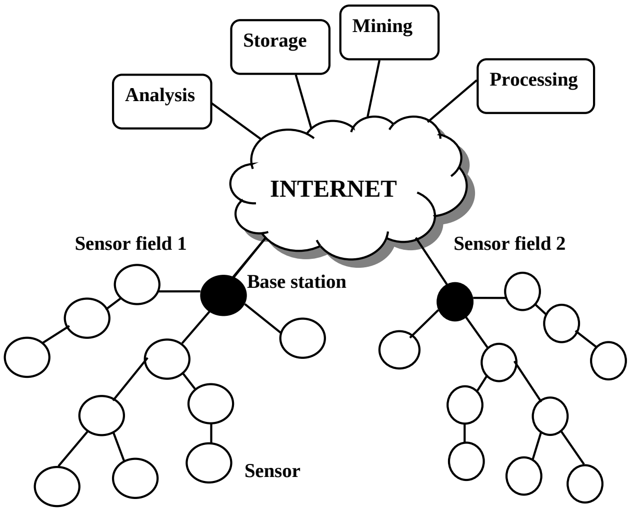

FIGURE 3.1: Wireless Sensor Network

proposed the concept of wireless integrated network sensors or WINS(Pottie 2001). The MIT μ AMPS (Micro Adaptive multi-domain Power aware sensors) project also focuses on low-power hardware and software components for sensor nodes, including the use of micro controllers capable of dynamic voltage scaling and techniques to reconstruct data processing algorithms to reduce power requirements at software level [Calhoun et al., 2005].

3.2 WSN Constraints

Constraints in Wireless Sensor Networks are as follows:-

3.2.1 Self-Management

It is the nature of many sensor network applications that they must operate in remote areas and harsh environments, without infrastructure support or possibility for maintenance and repair therefore, sensor nodes must be self-managing in that they configure themselves, operate and collaborate with other nodes.

3.2.2 Wireless Networking

The reliance on wireless networks and communications poses a number of challenges to a sensor network designer for eg, attenuation limits the range of radio signals, i.e., a radio frequency signal fades.

3.2.3 Decentralized Management

The large scale and energy constraints of many WSN make it infeasible to rely on centralized algorithms to implement network management solutions such as topology management or routing.

3.2.4 Design Constraints

While the capabilities of traditional computing systems continue to increase rapidly, the primary goal of WSN design to create smaller, cheaper, and more effective devices.

3.2.5 Security

Many WSN collect sensitive information. The remote and unattended operation of sensor nodes increases their exposure to malicious intrusions and attacks. As a consequence, sensor networks require new solutions for key establishment and distribution, node authentication, and secrecy.

3.3 PHASES OF WSN LOCALIZATION

WSN localization is two phase process:-

3.3.1 Measurement phase

The first of any WSN localization technique involves inter-node management of distances, angles or connectivity. The process of estimating node to node distances is also called ranging. Measurement techniques of WSN localization can be broadly classified into 4 categories: time-based measurements, angle of arrival (AOA) measurements, received signal strength measurements (RSSI), and proximity/network connectivity measurements.

1. **Time-based methods**: TOA, TDOA, RTT are popular time-based methods used for estimating distances between nodes in WSN. These methods can be translated directly into distances, based on the known signal propagation speed. TOA measures the sending time of the signal at the transmitter and signal at the receiver. For TOA-based ranging both transmitter and receiver clocks must be accurately synchronized and hence add the cost and complexities of such WSN transceivers.

2. **Received signal strength indicator**: RSSI method measures the power of signal at the receiver. Based on the known transmission power, the effective propagation loss can be calculated. Known radio propagation models are used for translating received signal strength into distances.

3. **Angle of arrival**: AOA measurement provides information about the direction of the incoming signal, and hence the angle between the two nodes. Though AOA based systems do not measure distance, they make use of direction information of the received signal and simple trignometric rules to calculate the node positions.

4. **Proximity connectivity measurements**: In proximity connectivity measurements, a sensor node measures which sensors are in its transmitting range. This is considered as simplest distance measurement technique there is no additional hardware requirement.

3.3.2 Position-based computation

In this phase position of the target nodes are determined by combining distance/angle estimates:

Trilateration: For the unique localization of a target node in 2D, it is sufficient to have the knowledge of distance between target node and three anchor nodes. Trilateration determines 2D coordinates of target node by calculating intersection of three circles shown in Fig. 3.2.

1. **Triangulation**: Triangulation is used for position computation when angle of node is estimated instead of distance. Target node positions are computed by using trignometric laws of sines or cosines shown in Fig. 3.3.

2. **Multilateration**: In multilateration target node position is estimated using distance measurements to three or more anchor nodes by minimizing error between actual distance and estimated distance in which one can consider the minimization of a function of range error as given below in Fig. 3.4

$$errorfunction = min \sum_{i} (D_{t_i} - \hat{D_{t_i}})^2 \tag{3.1}$$

where D_{t_i} is actual distance and the $\hat{D_{t_i}}$ is the estimated distance.

$$D_{t_i} = \sqrt{(x_t - x_i)^2 + (y_t - y_i)^2} \tag{3.2}$$

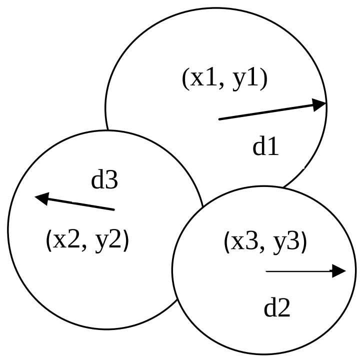

FIGURE 3.2: Trilateration

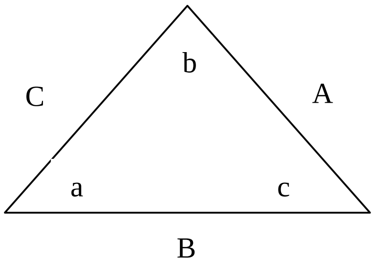

FIGURE 3.3: Triangulation

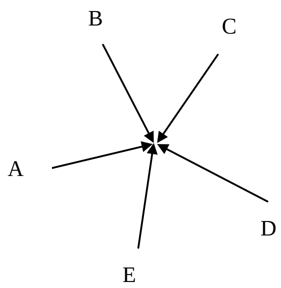

FIGURE 3.4: Multilateraton

3.4 Node Localization Taxonomy

WSN localization algorithm can be classified according to their design and implementation strategies such as: node connectivity, range information, anchor information and computation model. Location discovery algorithms may be classified according to several criteria, reflecting fundamental designs and implementation choices. Those different criteria form a reasonable taxonomy for characterizing and evaluation location discovery algorithms are shown in Fig. 3.5.

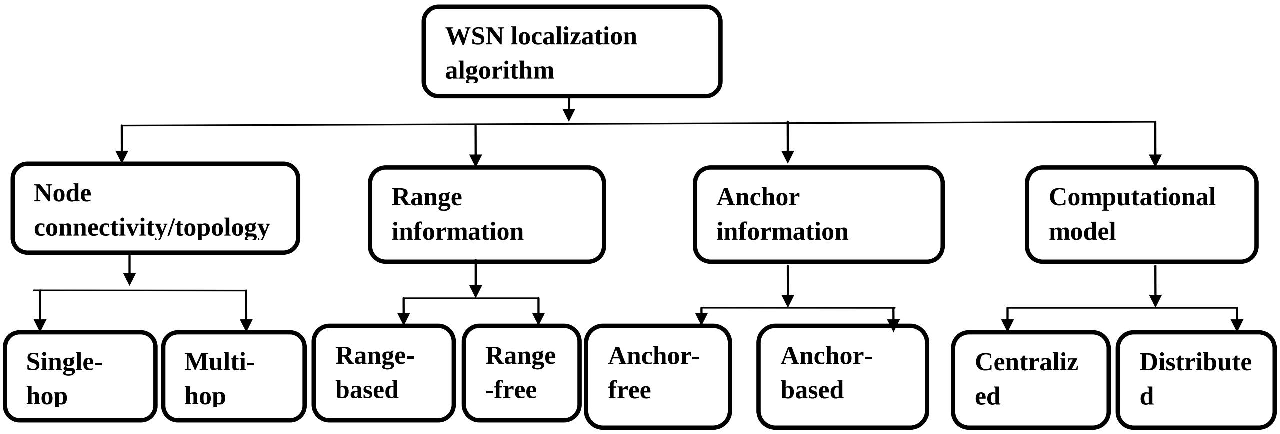

FIGURE 3.5: Taxonomy of localization schemes for sensor networks

In this different design alternatives for location discovery algorithms in general and in wireless sensor networks in particular. Localization is of most active research area in WSN. Localization usually refers to process of determining the positions of one or more nodes in large network. Many of the applications proposed for WSN require knowledge of origin of sensing information which gives rise to problem of localization.

3.4.1 Single hop versus multi-hop algorithm

Localization algorithms in which target nodes to be localized are within one-hop neighborhood of sufficient number of anchor nodes are called single hop algorithms.

When two nodes in a WSN are separated by a distance larger than radio range and node density is sufficiently high to create a continuous path between them such a path is called multi-hop path. In many WSN applications like wide area environment monitoring it is not always possible to have target nodes within one-hop neighborhood of anchor nodes. In this situation node rely on multi-hop localization as given below in Fig. 3.6.

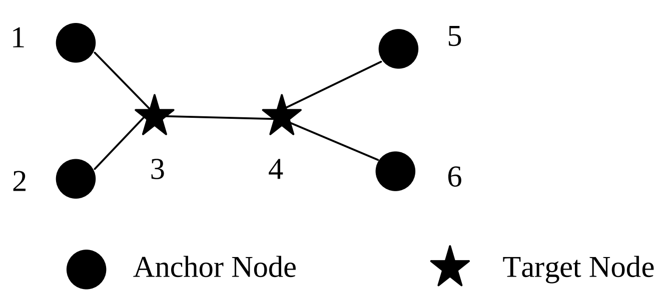

FIGURE 3.6: Multi-hop

3.4.2 Range-free versus range-based algorithm

Range-based localization schemes deploy complex and dedicated measurements mechanism to infer range information (in terms of distance of angle estimates) for calculating location of target nodes. Unlike range-based methods, range-free schemes does not require absolute range information for location estimation. Since indirect ranging metrics like number of hops can provide only coarse approximation of euclidean distances among sensor nodes, range-free algorithms are generally less accurate as compared to range-based.

3.4.3 Anchor-based versus anchor-based algorithms

Anchor-based algorithm rely on nodes (anchors or beacons) that are provided with their absolute position information either through manual configuration or by dedicated position finding mechanism like GPS. Goal of anchor-based algorithms are to determine absolute coordinates of target nodes using position information of anchor nodes.

Anchor-free are employed to find relative locations of sensor nodes from a set of geometric constraints extracted from range/proximity measurements.

3.4.4 Centralized versus distributed algorithms

In centralized algorithms inter-sensor distance information of entire network is to be communicated to central processor, where computation of target node coordinates are performed and coordinate information are to be forwarded back to nodes.

In distributed, single node (or group of nodes within same neighborhood) estimate its location using inter-sensor measurements and location information collected from anchor nodes within that neighborhood.

3.5 Conclusion

In this chapter, WSN, localization and WSN localization phases are discussed to enable reader to have some background knowledge about WSN. In this thesis, average localization error minimum will be target in upcoming chapter using BBO and its migration variants and PSO. Philosophy and algorithm flow of BBO and its migration variants are discussed in next chapter.

CHAPTER 4

BBO AND ITS VARIANTS

4.1 Introduction

BBO is one of the recently developed population based algorithms which has shown impressive performance over other Evolutionary Algorithms (EAs). BBO is a population based global optimization technique developed on the basis of science of biogeography, i.e., study of distribution of animals and plants among different habitats over time and space. The results of BBO are better as compared to other optimization techniques like Particle Swarm Optimization, Genetic algorithms, Ant Colony Optimization and Simulated annealing [Nan et al. [2007], Yun et al. [2009], Zhang et al. [2008b], Zhang et al. [2008a]].

4.2 Biogeography and BBO terminology

Basically biogeography was studied by Alfred Wallace [Wallace, 1876] and Charles Darwin [Darwin and Beer, 1869] mainly as descriptive study. In 1967, the work carried out by MacAurthur and Wilson [MacArthur and Wilson, 2001] changed this view point and proposed a mathematical model for biogeography and made it feasible to predict number of species in a habitat.

1. **Habitat:** In science of biogeography, habitat is an ecological area that is inhabited or covered by particular species of plants and animals. Habitat is any island that is geographical isolated from other islands. Therefore, we use generic term in place is

island. In BBO, the candidate solutions for problem are encoded as string as given by (4.1) and termed as habitats.

$$H = [SIV_1, SIV_2, ...SIV_M] \tag{4.1}$$

2. **Habitat Suitability Index:** It is measure of fitness or goodness of the solution which is represented as a habitat. Some habitats are more suitable for habitation than others.

3. **Suitability Index Variable:** Habitability is related to constituently factors of a habitat such as rainfall, temperature, diversity of vegetation etc. There are parameters or variables encoded in a string format (refer 4.1) to make habitats in BBO.

4. **Migration:** It is meant for the movement of species from one island or habitat to other for better comforts of living. In BBO, emigration and immigration terms are used that are related to migration of species from one island to other. Immigration is the replacement of an old solution feature is an individual with a new solution feature from another individual and Emigration is the sharing of a solution feature in BBO from one individual to another. The emigration solution feature remain in the emigrating individual.

4.3 BBO Characterization

It tell about relationship between immigration and emigration as shown in Fig. 4.1. Initially habitats with low HSI tend to have low emigration rate, μ, due to sparse population, however, they will have high immigration rate, λ. Suitability of habitats with low HSI is likely to increase the influx of species from other habitats having high HSI. However, if HSI does not increase and remains low species in that habitat go extinct that leads to additional immigration. It is safe to assume a linear relationship between HSI, immigration and emigration rates and same maximum emigration and immigration rates, i.e. , $E = I$ as depicted graphically in Fig 4.1. On the other side, habitats with high HSI tend to have large population of its resident species, that is responsible for more probability of emigration(emigration rate, μ) and less probability of immigration (immigration rate, λ) due to natural random behavior of species. Immigration is the arrival of new species into habitat or population, while emigration is the act of leaving one's native region.

For k-th habitat, i.e., HSI_k, values of emigration rate and immigration rate are given by (4.2) and (4.3).

$$\mu_k = E \cdot \frac{HSI_k}{HSI_{max} - HSI_{min}} \tag{4.2}$$

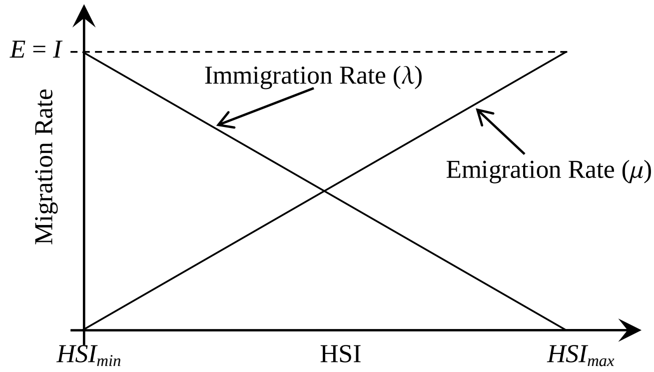

FIGURE 4.1: BBO Charactersitics

$$\lambda_k = I \cdot \left(1 - \frac{HSI_k}{HSI_{max} - HSI_{min}}\right) \tag{4.3}$$

The immigration of new species from high HSI to low HSI habitats may raise the HSI of poor habitats as good solution have more resistance to change than poor solutions whereas poor solutions are more dynamic and accept a lot of new features from good solutions. Each habitat in a population of size NP, in BBO, is represented by M-dimensional vector as $H = [SIV_1, SIV_2, ...SIV_M]$ whereas M is the number of SIVs (features) to be evolved for optimal HSI. HSI is the degree of acceptability that is determined by evaluating the cost/objective function, i.e., $HSI = f(H)$. In BBO, it involves two mechanisms of algorithm flow, i. e., (1)migration and (2)mutation, these are discussed as follows in further sections.

4.4 Migration Variant Algorithms for BBO

Migration is the probabilistic operator that improves HSI of poor habitats by sharing features from good habitats. During migration, i-th habitat, H_i where $(i = 1, 2, ...NP)$ use its immigration rate λ_i, given by (4.3) to probabilistically decide whether to immigrate or not. In case immigration is selected, then the emigrating habitat, H_j, is found probabilistically based on emigration rate, μ_j, given by (4.2). The process of migration is computed by copying values of SIVs from H_j to H_i at random chosen sites, i.e., $H_i(SIV) \leftarrow H_j(SIV)$. The pseudo code of migration is depicted in Algorithm 1.

Migration may lead to same types of habitats because of copying SIVs or features from habitats having high HSI to low HSI habitat. To reduce number of same types of habitats and make BBO convergence faster, migration variants are introduced. BBO has three migration variants that are discussed as follows

1. Blended Migration

2. Immigration Refusal
3. Enhanced Biogeography-Based Optimization

Algorithm 1 Pseudo Code for Migration

```
for i = 1 to NP do
    Select H_i with probability based on λ_i
    if H_i is selected then
        for j = 1 to NP do
            Select H_j with probability based on μ_j
            if H_j is selected
                Randomly select a SIV(s) from H_j
                Copy them SIV(s) in H_i
            end if
        end for
    end if
end for
```

4.4.1 Blended Migration

Blended Migration operator is a generalization form of the standard BBO migration operator and inspired by blended crossover in GAs [McTavish and Restrepo, 2008]. In blended migration, a solution feature of solution H_i is not simply replaced by a feature from solution H_j that happened in standard BBO migration operator. Instead, a new solution feature, in blended migration, solution is comprised of 2 component, the migration of a feature from another solution and migration of feature from itself, i.e., $H_i(SIV) \leftarrow \alpha \cdot H_i(SIV) + (1-\alpha) \cdot H_j(SIV)$ where α is the random number between 0 and 1. The pseudo code of blended migration is depicted as Algorithm 2.

4.4.2 Immigration Refusal

In BBO, if a habitat has high emigration rate, i.e., the probability of emigrating to other habitats is high and the probability of immigration from other habitats is low. Once in a while, a highly fit solution with migrate solution features from a low fit solution to high fit solution. This may degrade the high fitness of the habitats which receives immigrants. If high fitness of solution decrease after receiving the immigrants, then immigrating habitat may refuse the immigrating solution features. This BBO variants with conditional migration is termed as immigration refusal [Du et al., 2009] and is depicted in Algorithm 3.

Algorithm 2 Pseudo Code for Blended Migration

```
for i = 1 to nH do
    Select H_i with probability based on λ_i
    if H_i is selected then
        for j = 1 to nH do
            Select H_j with probability based on μ_j
            if H_j is selected
                H_i(SIV) ← α • H_i(SIV) + (1 − α) • H_j(SIV)
            end if
        end for
    end if
end for
```

Algorithm 3 Pseudo Code for Immigration Refusal

```
Select ImHbt with probability based on λ
if ImHbt is selected then
    Select EmHbt with probability based on μ
    if EmHbt is selected then
        if (Option = = Standard or Immigration Refusal or EBBO)
        Randomly select a SIV(s) from EmHbt
        Copy them SIV(s) in ImHbt
         switch (Option)
          case: Immigration Refusal
            if (fitness(ImHbt)>fitness(EmHbt))
              apply migration
            end if
          case: EBBO
            eliminate duplicates
          case: Blended
          ImHbt (SIV) ← α • ImHbt (SIV) + (1 − α) • EmHbt (SIV)
         end switch
        end if
    end if
end if
```

4.4.3 Enhanced Biogeography-Based Optimization

Standard BBO migration operator creates the duplicate solutions which decreases the diversity of algorithm. To prevent the harmful over similarity among the solutions, clear duplicate operator with random mutation is utilized, i.e., EBBO [Pattnaik et al., 2010], depicted in Algorithm 3, increases the exploration ability.

4.5 Mutation

It is another probabilistic operator that randomly modifies the values of some randomly selected SIVs that is intended for exploration of search space for better solution by increasing the biological diversity in population. The pseudo code of mutation is depicted in Algorithm 4.

Algorithm 4 Pseudo Code for Mutation

$mRate = C \times \min(\mu_k, \lambda_k)$ where $C = 3$
for n = 1 to NP **do**
  for j = 1 to length(H) **do**
    Select H_j(SIV) with $mRate$
    If H_j(SIV) is selected **then**
      Replace H_j(SIV) with randomly generated SIV
    end if
  end for
end for

4.6 Conclusion

Here, in this chapter, philosophy of biogeography and inspired algorithms with different migration variants are discussed. These migration variants are experimented in minimizing average localization error in application of WSN. The philosophy of PSO is presented in next chapter.

CHAPTER 5

PARTICLE SWARM OPTIMIZATION

5.1 Introduction

Since early 90's investigations on new optimization techniques, based on the analogy of social behavior of swarms of natural creatures, have been started. Eberhart and Kennedy developed PSO [Kennedy and Eberhart, 1995] based on the analogy of bird flock and fish school, where each individual is allowed to learn from experiences of its own and others.

PSO is a swarm based optimization tool which is useful like other EAs, to evolve near optimum solution to a problem. The evolution is initiated with a set of randomly generated potential solutions and then is allowed to search for optimum one, iteratively. It searches the optimum solution by observing the best performing particles. As compared to GAs, the PSO has much intelligent background and could be performed more easily [Shi et al., 2007]. Due to its advantages, the PSO is not only suitable for scientific research, but also engineering applications. PSO has attracted broad attention in the fields of EC, optimization and many others [Clerc and Kennedy, 2002], [Angeline, 1998], [Trelea, 2003], [Chu et al., 2003]. Although the PSO is developed for continous optimization problems, however, investigations studies have been reported that are focussed on discrete problems as well [Kennedy and Eberhart, 1997]. PSO is a robust stochastic optimization technique based on the movement and intelligence of swarms. It uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution. Each particle keeps track of its coordinates in the solution space which are associated with the best solution (fitness) that has achieved so far by that particle. It is further described as follows:-

1. PSO applies the concept of social interaction to problem solving.
2. It was developed in 1995 by James Kennedy (social-psychologist) and Russell Eberhart (electrical engineer).
3. It uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution.
4. Each particle keeps track of its coordinates in the solution space which are associated with the best solution (fitness) that has achieved so far by that particle. This value is called personal best, pbest.
5. Another best value that is tracked by the PSO is the best value obtained so far by any particle in the neighborhood of that particle. This value is called gbest.
6. The basic concept of PSO lies in accelerating each particle toward its pbest and the gbest locations, with a random weighted accelaration at each time step.

5.2 Particle Swarm Optimization

PSO is a robust stochastic optimization technique based on the movement and intelligence of swarms. PSO applies the concept of social interaction to problem solving. It was developed in 1995 by James Kennedy (social-psychologist) and Russell Eberhart (electrical engineer). It uses a number of agents (particles) that constitute a swarm moving around in the search space looking for the best solution. Each particle keeps track of its coordinates in the solution space which are associated with the best solution (fitness) that has achieved so far by that particle. This value is called personal best, *pbest*. Another best value that is tracked by the PSO is the best value obtained so far by any particle in the neighborhood of that particle. This value is called *gbest*. The basic concept of PSO lies in accelerating each particle toward its *pbest* and the *gbest* locations, with a random weighted acceleration at each time step as shown in Fig. 5.1.

Later on, it was realized that the simulation could be used as an optimizer and resulted in the first simple version of PSO. In PSO, the particles have (1) adaptable velocities that determines their movement in the search space, (2) memory which enable them for remembering the best position in the search space ever visited. The position corresponding to the best fitness is known as past best, *pbest*, and the overall best out of all NP the particles in the population is called global best, *gbest*. Consider that the search space is M-dimensional and i-th particle location in the swarm can be represented by $X_i = [x_{i1}, x_{i2}, ...x_{id}..., x_{iM}]$ and its velocity can be represented by another M-dimensional vector $V_i = [v_{i1}, v_{i2}, ...v_{id}.., v_{iM}]$. Let the best previously visited location position of this particle be denoted by $P_i = [p_{i1}, p_{i2}, ...p_{id}.., p_{iM}]$, whereas, g-th particle, i.e., $P_g = [p_{g1}, p_{g2}, ...p_{gd}.., p_{gM}]$, is globally best particle location. Fig. 5.1 depicts the vector movement of particle element from location x^n_{id} to x^{n+1}_{id} in $(n+1)$-th iteration that is being governed by past best location, p^n_{id}, global best location, p^n_{gd}, and current velocity v^n_{id}. Alternatively, the whole swarm is updated according to the equations (5.1) and (5.2) suggested by [Hu et al., 2004], [del Valle et al., 2008].

$$v^{m+1}_{id} = \chi(wv^m_{id} + \psi_1 r_1(p^m_{id} - x^m_{id}) + \psi_2 r_2(p^m_{gd} - x^m_{id})) \tag{5.1}$$

$$x^{m+1}_{id} = x^m_{id} + v^{m+1}_{id} \tag{5.2}$$

Here, w is inertia weight, ψ_1 is cognitive learning parameter, ψ_2 is social learning parameter and constriction factor, χ, are strategy parameters of PSO algorithm, while r_1 and r_2 are random numbers uniformly distributed in the range [0,1]. Generally the inertia weight, w, is not kept fixed and is varied as the algorithm progresses. The particle movements is restricted with maximum velocity, $\pm V_{max}$, to avoid jump over the optimal location as per search space requirements.

The PSO characteristics is given below in Fig. 5.1

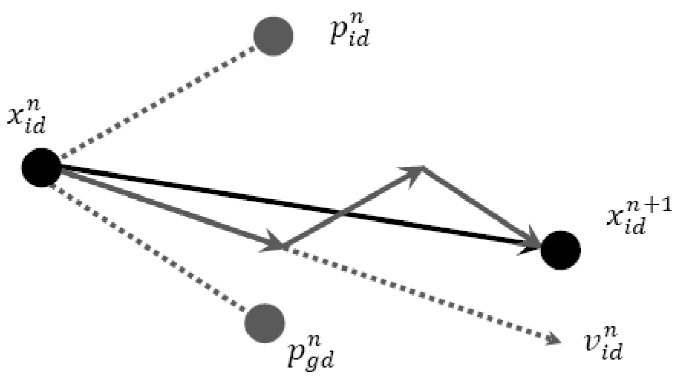

FIGURE 5.1: PSO Characteristics

In this PSO model each particle is free to interact with its present *pbest* and *gbest* particles as described in (5.1) and (5.2). The parameter V_{max} is the maximum velocity along any dimension which implies that, if velocity along any dimension exceeds V_{max}, it shall be clamped to this value to avoid search explosion. The inertia weight w, governs how much of velocity should be retained from previous time step.

5.3 Pseudo Code for PSO

The Pseudo code for PSO is given below in Algorithm 5

Algorithm 5 Pseudo Code for PSO

Initialize w_1, c_1 and c_2
Initialize maximum allowable iterations $m_{\max}$
Initialize the target fitness f_T
Initialize $x_{\min}$, $x_{\max}$, $v_{\min}$ and $v_{\max}$
for each particle i **do**
    for each dimension d **do**
        Initialize x_{id} randomly : $x_{\min} \leq x_{id} \leq x_{\max}$
        Initialize v_{id} randomly : $v_{\min} \leq v_{id} \leq v_{\max}$
    end for
end for
Iteration $m = 0$
while $(m \leq m_{\max})$ AND $f(p_g) > f_T$ **do**
    for each particle i **do**
        Compute $f(x_i)$
        if $f(x_i) < f(p_i)$ **then**
            for each dimension d **do**
                $p_{id} = x_{id}$
            end for
        end if
        if $f(x_i) < f(p_g)$ **then**
            for each dimension d **do**
                $p_{gd} = x_{id}$
            end for
        end if
    end for
    for each particle i **do**
        for each dimension d **do**
            Compute velocity v_{id}^{m+1} using (5. 1)
            Restrict v_{id} to $v_{\min} \leq v_{id} \leq v_{\max}$
            Compute position x_{id}^{m+1} using (5. 2)
            Restrict x_{id} to $x_{\min} \leq x_{id} \leq x_{\max}$
        end for
    end for
    $m = m + 1$
end while

5.4 Conclusion

In this chapter, philosophy of Particle Swarm Optimization algorithm are discussed. Particle Swarm Optimization is experimented in minimizing average localization error in application of WSN. Localization in Simulation Environment, various implementation steps using PSO, BBO and its migration variants with Qt creator are presented in next chapter.

CHAPTER 6

LOCALIZATION IN SIMULATION ENVIRONMENT

6.1 Introduction

To determine node localization in WSN is complex optimization problem. The goal of the localization process is to determine actual position of the nodes with minimum error. Few performance parameters are transmitting radius, deployment of the anchor and target nodes, actual and estimated distance, computed time and error. To minimize error in WSN, BBO and its migration variants and PSO are experimented and investigated for faster convergence and actual positions with less error. QT Creator is used to create BBO algorithm, PSO algorithm in C++.

6.2 Implementation Requirements

To minimize error in WSN using BBO and PSO requires QT Creator for C++ programming and MATLAB for plotting graphs. Their brief introduction presents in following subsection:

6.2.1 Simulation Platforms

The Qt framework first became publicly available in May 1995. It was initially developed by Haavard Nord (Trolltech's CEO) and Eirik Chambe-Eng (Troll-Tech's president). Haavard's interest in C++ GUI development began in 1988 when he was commissioned by a Swedish company to develop a C++ GUI framework. Programming can be lot like filling in travel reimbursement forms, only worse. Qt is comprehensive C++ framework for developing cross-platform GUI application using a "write once, compile anywhere approach". Qt lets programmer use a single source tree for applications that will run on Window 98 to XP, Mac OSX, Linux, Solaris and many other versions of Unix with X11. It has many features that are discussed as follows:

1. Making Connections
2. Laying out Widgets
3. Creating custom Widgets
4. 2D and 3D graphics
5. Layout Management
6. Implementing application functionality
7. Providing online help
8. Internationalization
9. Interfacing with Native APIs
10. Handling X11 Session Management

6.3 Flow Chart

To determine actual position of nodes in distributed area the process of localization using BBO and PSO is described in form of flow chart that is described as below Fig. 6.1:

1. N target nodes and M anchor nodes are randomly deployed in a 2-Dimensional sensor field. Each target node and anchor node has a transmission range R. At each iteration one node gets settled and works as anchor node in the next iteration and transmits information as the anchors do.
2. Target node which has atleast 3 anchor nodes in its transmission range is said to be localized.
3. Mean of coordinates of anchor nodes fall within transmission range, i.e., mean $(x_1, x_2, ...x_5..., x_n)$, mean $(y_1, y_2, ...y_5..., y_n)$ is termed as centroid position.

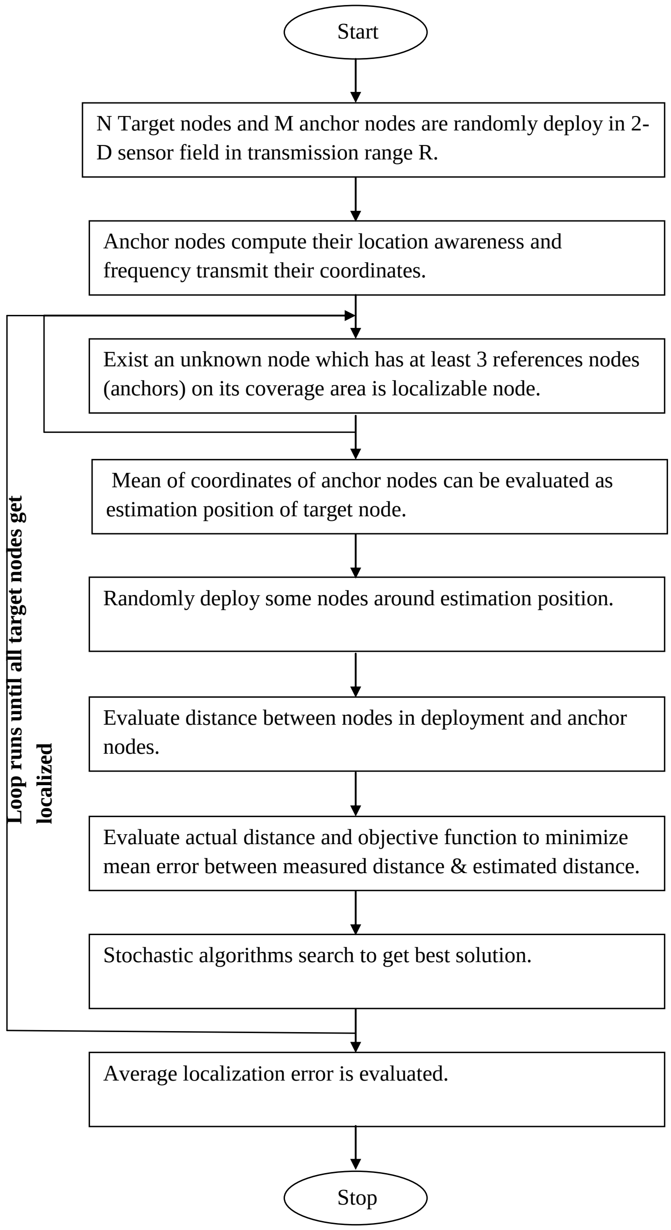

Figure 6.1: Flow Diagram for Localization

4. Randomly deploy few nodes around estimated position and distance between nodes in deployment and anchor nodes in the transmission range are calculated. The distance measurement are effected with gaussian additive noise. A node estimates its distance from anchor i as $\hat{d_i} = d_i + \eta_i$. Where d_i is the actual distance and given by following equation

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{6.1}$$

where (x, y) is the location of target node and (x_i, y_i) is the location of i-th anchor node in neighborhood of target node. The measurement noise η_i has a random value which is uniformly distributed in the range $d_i \pm d_i \frac{(P_n)}{100}$ where P_n is percentage noise in distance measurement.

5. Five case studies are conducted . Each localization target node runs PSO, BBO, Blended BBO, EBBO and Immigration Refusal to localize itself. The objective function is to minimize the average localization error between measured distance and estimated distance. It is defined as follows

$$f(x,y) = \frac{1}{M}\sum_{i=1}^{M}(\sqrt{(x-x_i)^2+(y-y_i)^2} - \hat{d}_i)^2 \tag{6.2}$$

where $M \geq 3$ is the number of anchor nodes within transmission range R, of target node.

6. When all the N_l localizable nodes determine their coordinates, total average localization error is calculated as the mean of square of distances of estimated node coordinates (x_i, y_i) and the actual node coordinates (X_i, Y_i), for $i = 1, 2, 3...N_l$, determines for all cases of PSO, BBO, Blended BBO, EBBO, Immigration Refusal in following equation

$$E_l = \frac{1}{N_l}\sum_{i=1}^{M}((x_i - X_i)^2 + (y_i - Y_i)^2) \tag{6.3}$$

7. Steps 2 to 6 are repeated until all target nodes get localized. The performance of localization algorithm is based on E_l and N_{Nl}, where $N_{Nl} = N$ - N_l is number of nodes that could not be localized. The minimum the values of E_l and N_{Nl}, the better will be the performance.

6.4 Simulation Scenarios

Localization Simulation and its performance are conducted by using PSO, BBO and its migration variants. The parameters of PSO are set as follows:

1. Population = 10, iterations=20
2. Acceleration constants $c_1 = c_2 = 2.0$
3. Limits on particle position: X_{min}=0 and X_{max}=100
4. Anchors=10 and 15
5. Transmitting Range=25, 20 and 15

25 trial experiments of PSO-based localization are conducted for P_n=2 and P_n=5.

Parameters of BBO and its migration variants as set as follows:

1. Population = 10, iterations=20
2. Limits on particle position: X_{min}=0 and X_{max}=100
3. w=0.01
4. Anchors=10 and 15
5. Transmitting Range=25, 20 and 15

25 trial experiments of Biogeography-based localization and its migration variants are conducted for P_n=2 and P_n=5

6.5 Conclusion

In this chapter, various implementation steps of flow of localization using BBO and PSO with QT creator. Software are discussed for better understanding of work. Simulation results of performance of BBO migrants and PSO are represented in next chapter.

CHAPTER 7

SIMULATION RESULTS

7.1 Introduction

WSN localization simulations and its performance evaluation were conducted using PSO, BBO, Blended BBO, EBBO, Immigration Refusal in QT Creator. 50 target nodes and 10 and 15 anchor nodes are randomly deployed in 2-dimensional sensor field having dimensions of 100×100 square units. Each anchor has a transmission range of R=25, 20 and 15 units. Strategic settings specific to case study of PSO, BBO, Blended BBO, EBBO, Immigration Refusal alogorithms as discussed below.

7.1.1 Particle Swarm Optimization

Each target node that can be localized, runs PSO algorithm to localize itself. The parameters of PSO are set as follows.

1. Population = 10, iterations=20

2. Acceleration constants $c_1 = c_2 = 2.0$

3. Limits on particle position: X_{min}=0 and X_{max}=100

4. Anchor nodes=10 and 15

5. Transmitting Range=25, 20 and 15

25 trial experiments of PSO-based localization are conducted for P_n=2 and P_n=5. Average of total localization error E_l defined in chapter 6 is computed. Localization estimated by PSO of range=25, 20 and 15 with anchor nodes=10 are shown in Fig. 7.1-Fig. 7.3 and localization estimated by PSO of range=25 with anchor nodes=15 is shown in Fig. 7.4

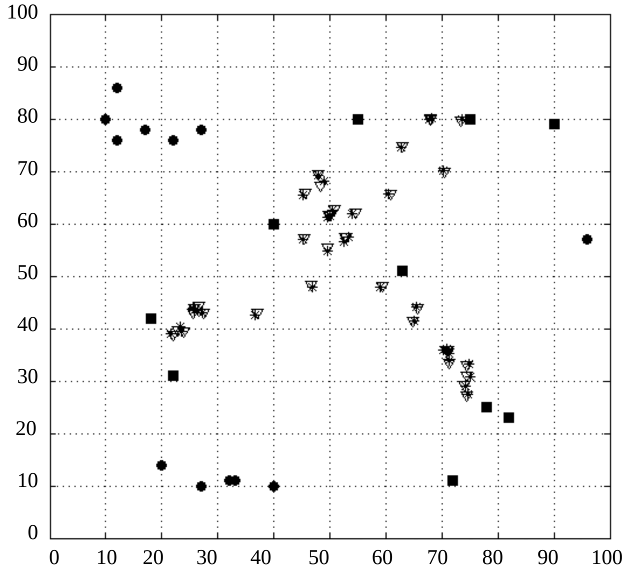

FIGURE 7.1: Localization Estimated by PSO for Transmitting Range=25

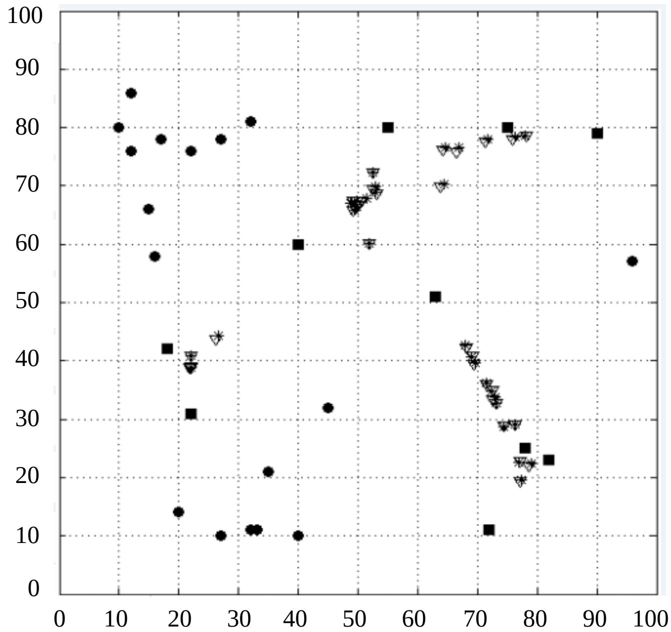

FIGURE 7.2: Localization Estimated by PSO for Transmitting Range=20

whereas, ∇ defines localization estimated by PSO, BBO and its migration variants respectively, ■ defines location of anchor nodes, $*$ defines location of node, • defines non-localized nodes in Fig. 7.1 - Fig. 7.20.

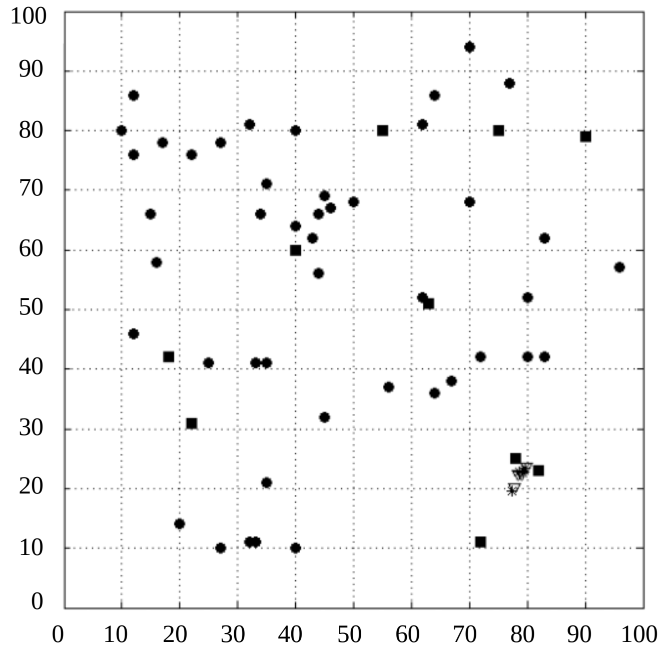

FIGURE 7.3: Localization Estimated by PSO for Transmitting Range=15

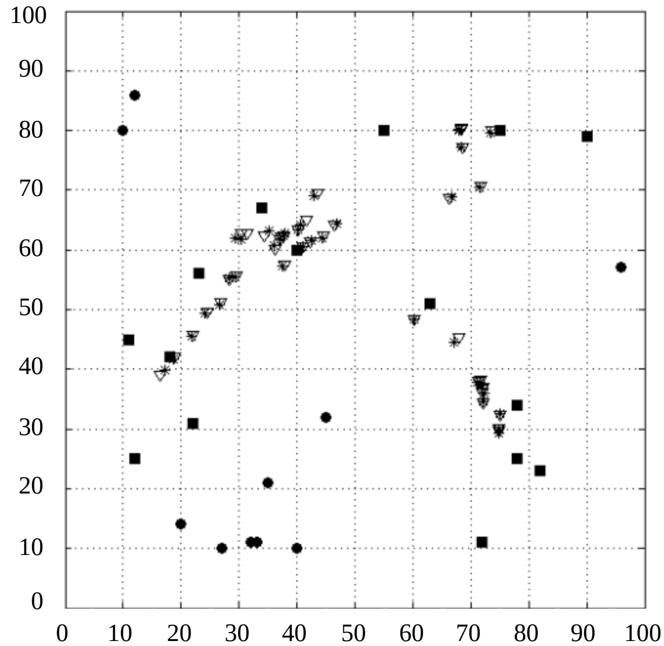

FIGURE 7.4: Location estimated by PSO for Anchors=15 with Transmitting Range=25

7.1.2 BBO and its Variants

Each target node that can be localized, runs BBO algorithm to localize itself. The parameters of BBO and its migration variants are set as follows.

1. Population = 10, iterations 20
2. Limits on particle position: X_{min}=0 and X_{max}=100 and Y_{min}=0 and Y_{max}=100
3. inertia weight w=0.01
4. Anchor nodes=10 and 15
5. Transmitting Range=25, 20 and 15

25 trial experiments of Biogeography-based localization are conducted for P_n=2 and P_n=5. Average of total localization error E_l defined in chapter 6 is computed. The parameters are similar for Case 3, Case 4, Case5 of Blended BBO, EBBO, Immigration Refusal respectively, and each target node that can be localized, runs Blended BBO, EBBO, Refusal BBO algorithm to localize itself. Localization estimated by BBO and its migration variants of range=25, 20 and 15 with anchor nodes=10 are shown in Fig. 7.5 - Fig. 7.7, Fig. 7.9 - Fig. 7.11, Fig. 7.13 - Fig. 7.15, Fig. 7.17 - Fig. 7.19 and localization estimated by BBO and its migration variants with range=25 for anchor nodes=15 are shown in Fig. 7.8, Fig. 7.12, Fig. 7.16, Fig. 7.20.

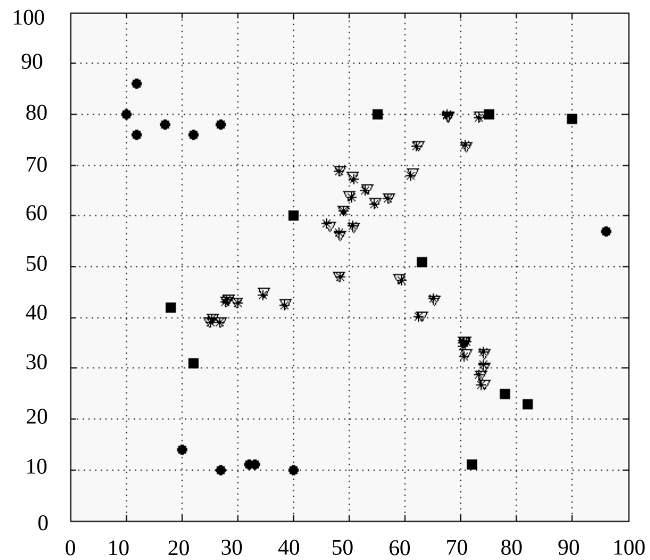

FIGURE 7.5: Localization Estimated by BBO for Transmitting Range=25

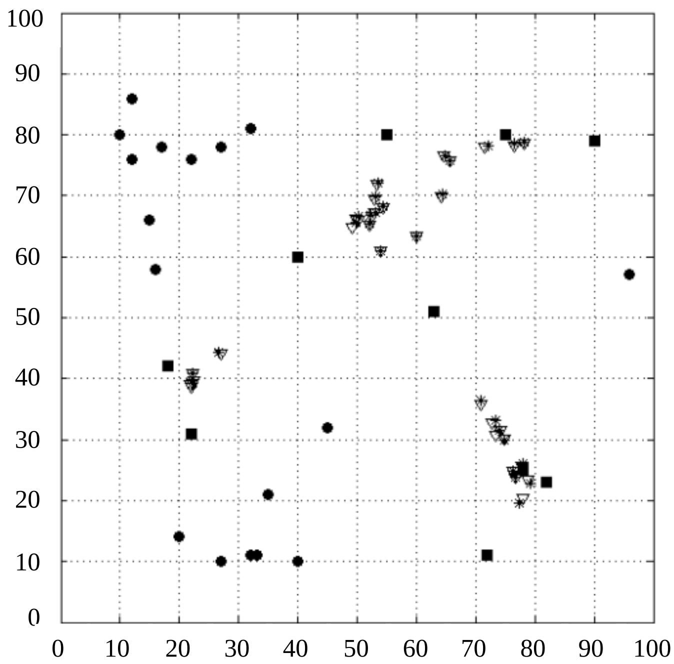

FIGURE 7.6: Localization Estimated by BBO for Transmitting Range=20

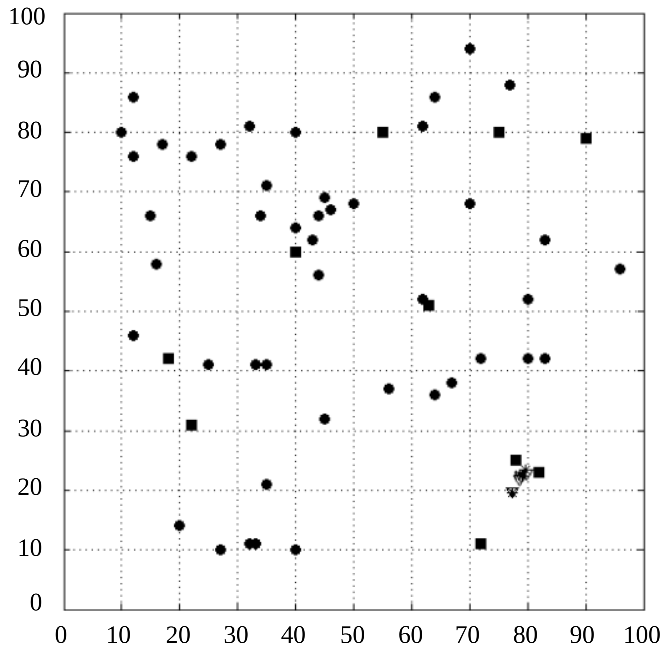

FIGURE 7.7: Localization Estimated by BBO for Transmitting Range=15

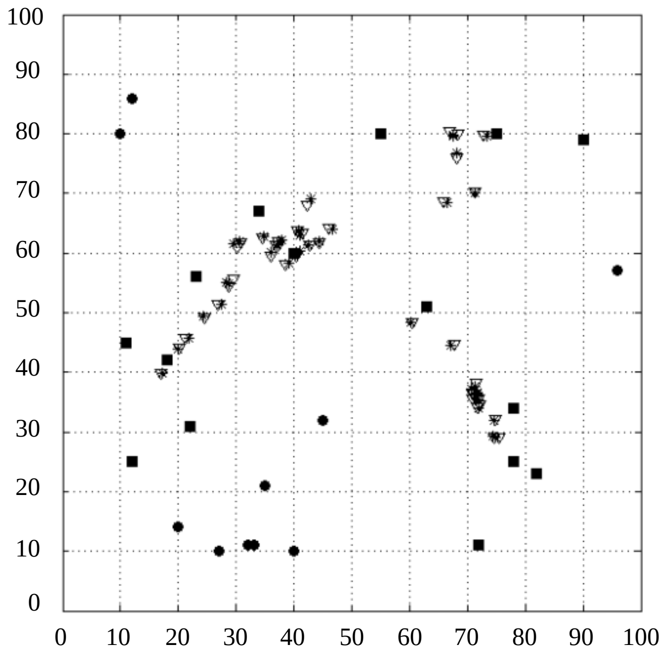

FIGURE 7.8: Location estimated by BBO for Anchors=15 with Transmitting Range=25

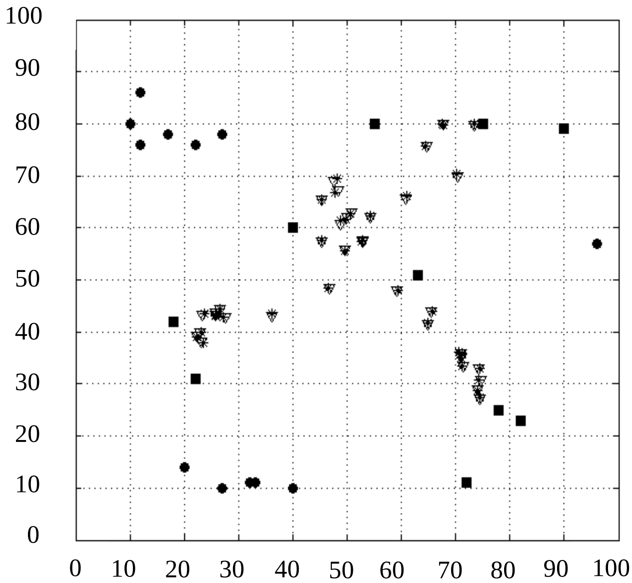

FIGURE 7.9: Localization Estimated by Blended BBO for Transmitting Range=25

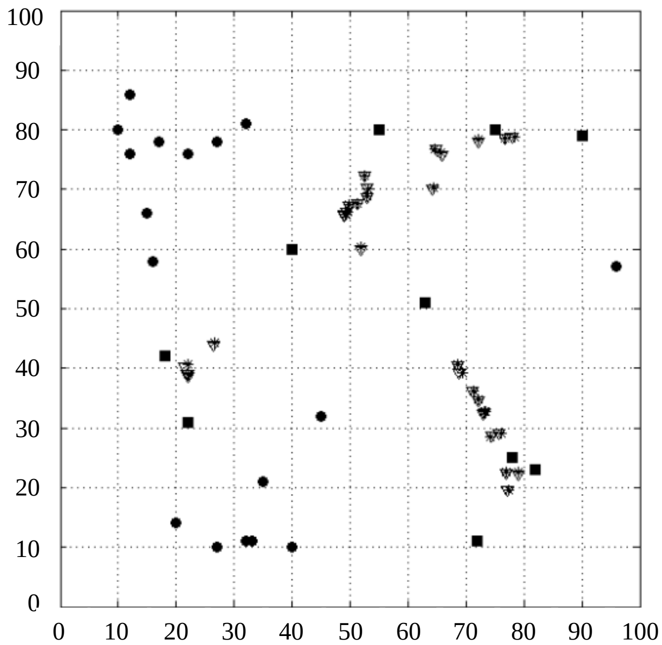

FIGURE 7.10: Localization Estimated by Blended BBO for Transmitting Range=20

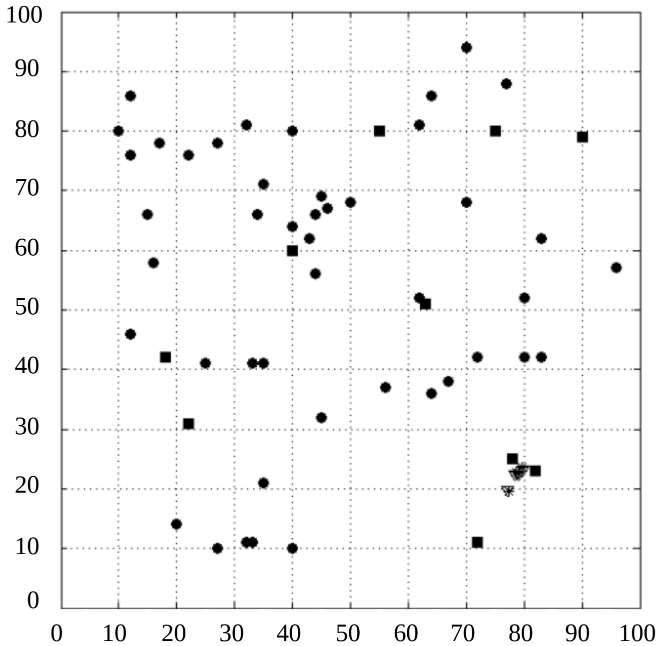

FIGURE 7.11: Localization Estimated by Blended BBO for Transmitting Range=15

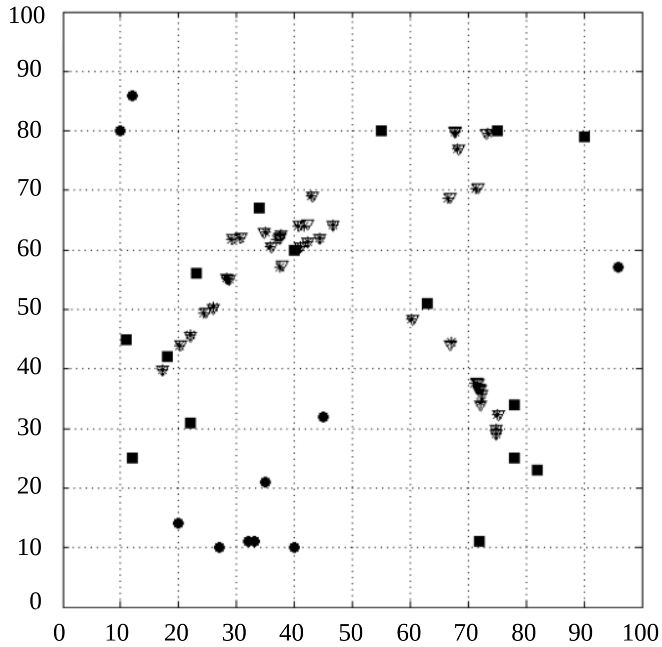

Figure 7.12: Location estimated by Blended BBO for Anchors=15 with Transmitting Range=25

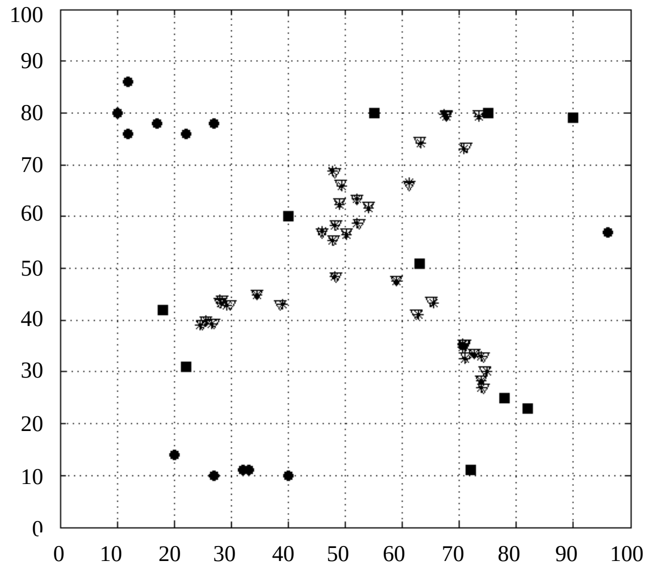

Figure 7.13: Localization Estimated by EBBO for Transmitting Range=25

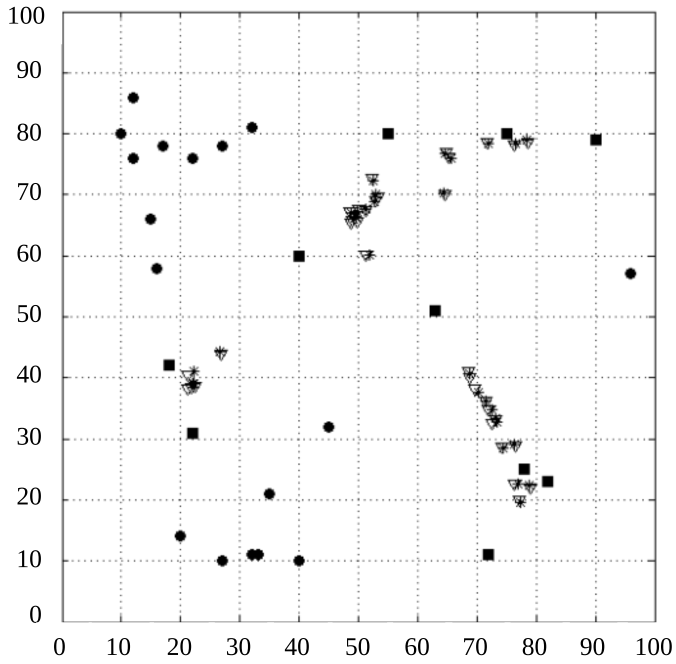

FIGURE 7.14: Localization Estimated by EBBO for Transmitting Range=20

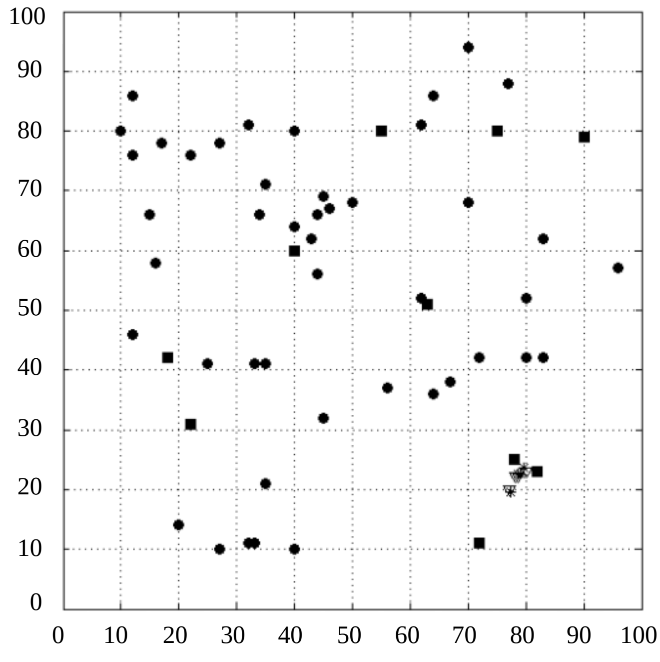

FIGURE 7.15: Localization Estimated by EBBO for Transmitting Range=15

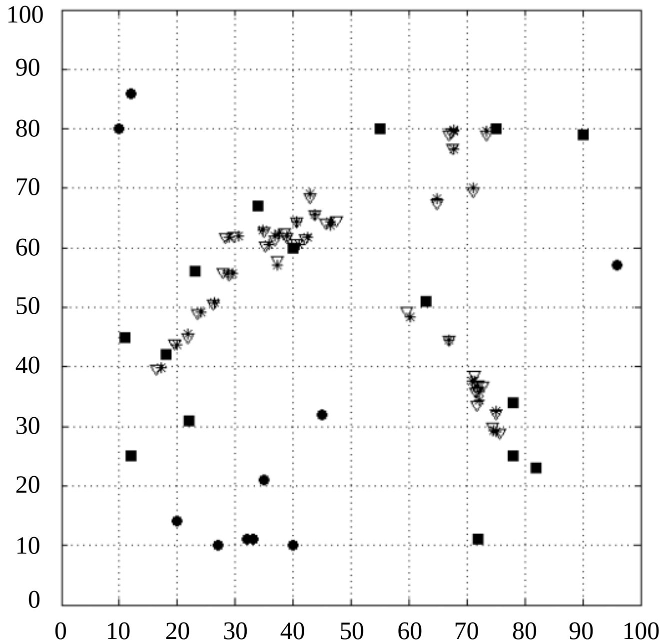

FIGURE 7.16: Location estimated by EBBO for Anchors=15 with Transmitting Range=25

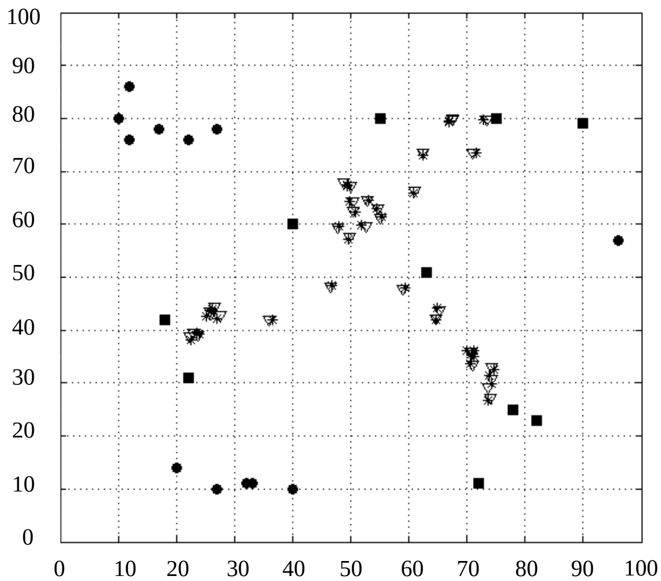

FIGURE 7.17: Localization Estimated by Immigration Refusal for Transmitting Range=25

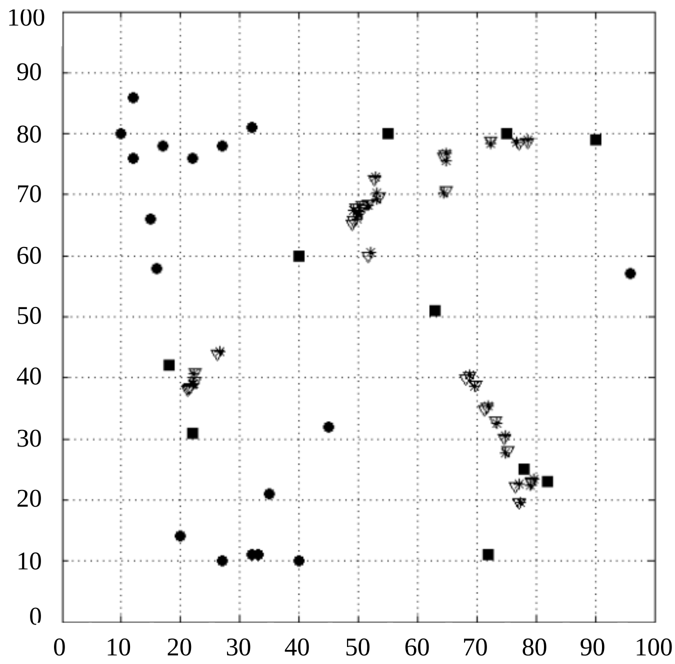

FIGURE 7.18: Localization Estimated by Immigration Refusal for Transmitting Range=20

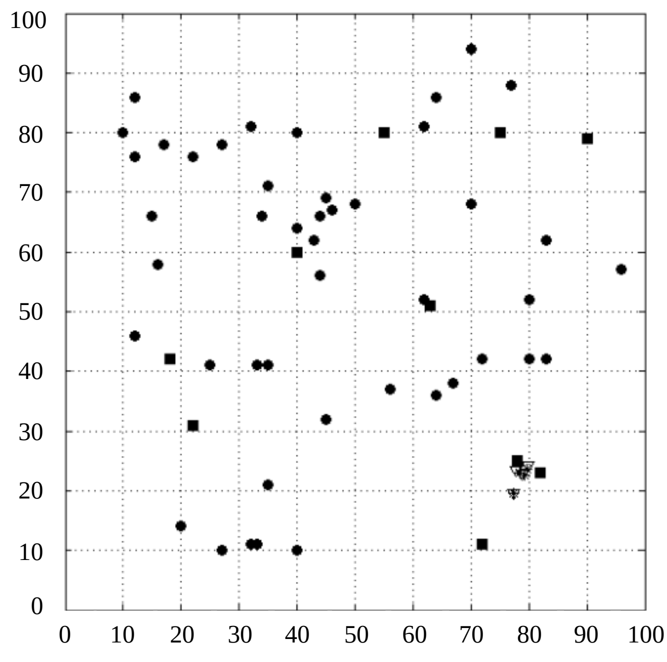

FIGURE 7.19: Localization Estimated by Immigration Refusal for Transmitting Range=15

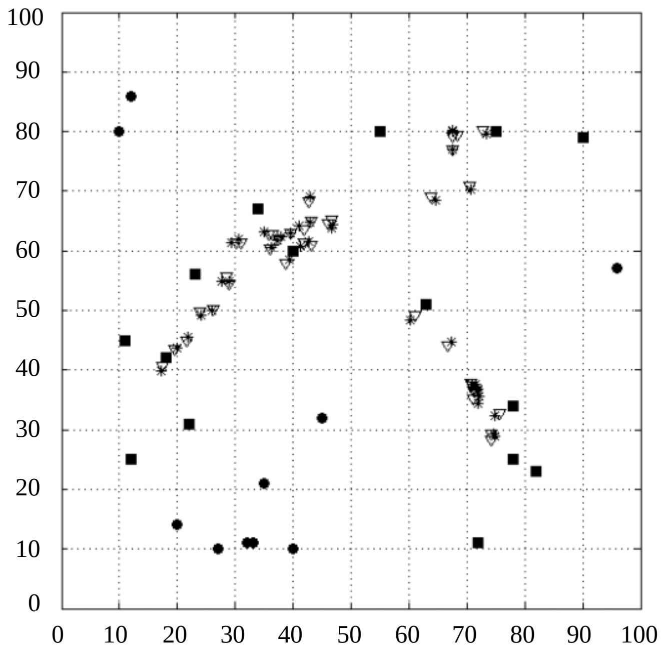

FIGURE 7.20: Location estimated by Immigration Refusal for Anchors=15 with Transmitting Range=25

TABLE 7.1: A Summary of Results of 25 Trial Runs PSO, BBO, Blended BBO, EBBO, Immigration Refusal for Transmitting Range=25

	P_n =2		P_n =5	
EAs	**E_l**	**Time(s)**	**E_l**	**Time(s)**
PSO	0. 33632	0.743	0. 50465	0.733
BBO	0. 52196	0.629	0. 75640	0.602
Blended BBO	**0. 25517**	0.635	**0. 36346**	0.621
EBBO	0. 47887	0.625	0. 66613	0.648
Refusal BBO	0. 58870	0.623	0. 66914	0.638

7.1.3 Overall Result Tabulation

The actual locations of nodes and anchors, and the coordinates of the nodes estimated by PSO, BBO, Blended BBO, EBBO, Immigration Refusal in a trail run are shown in Fig. 6.1 - Fig. 7.19. Results of PSO, BBO, Blended BBO, EBBO, Immigration Refusal based localization for ranges=25, 20 and 15 with anchor nodes are summarized in Table 7.1, Table 7.2 and Table 7.3 and results of PSO, BBO, Blended BBO, EBBO and Immigration Refusal based localization for range=25 with anchor nodes=15 are summarized in Table 7.4 shows that all stochastic algorithms used here have performed fairly well in WSN localization.

TABLE 7.2: A Summary of Results of 25 Trial Runs PSO, BBO, Blended BBO, EBBO, Immigration Refusal for Transmitting Range=20

	P_n =2		P_n =5	
EAs	E_l	**Time(s)**	E_l	**Time(s)**
PSO	0. 4839	0.620	0. 5777	0.618
BBO	0. 5361	0.484	0. 6692	0.547
Blended BBO	**0. 2564**	0.502	**0. 3725**	0.438
EBBO	0. 5877	0.469	0. 6594	0.508
Refusal BBO	0. 6204	0.556	0. 7983	0.518

TABLE 7.3: A Summary of Results of 25 Trial Runs PSO, BBO, Blended BBO, EBBO, Immigration Refusal for Transmitting Range=15

	P_n =2		P_n =5	
EAs	E_l	**Time(s)**	E_l	**Time(s)**
PSO	0. 5486	0.060	0. 6133	0.073
BBO	0. 6403	0.075	0. 8318	0.052
Blended BBO	**0. 3440**	0.069	**0. 4005**	0.068
EBBO	0. 6219	0.067	0. 7002	0.070
Refusal BBO	0. 7107	0.053	0. 7237	0.067

TABLE 7.4: A Summary of Results of 25 Trial Runs PSO, BBO, Blended BBO, EBBO, Immigration Refusal for Anchors=15 with Transmitting Range=25

	P_n =2		P_n =5	
EAs	E_l	**Time(s)**	E_l	**Time(s)**
PSO	0. 3590	0.783	0. 5025	0.769
BBO	0. 5176	0.684	0. 5814	0.648
Blended BBO	**0. 2343**	0.703	**0. 2620**	0.725
EBBO	0. 5890	0.679	0. 6150	0.722
Refusal BBO	0. 5616	0.691	0. 6180	0.702

7.2 Conclusion

In this chapter, Artificial intelligence based single-hop distributed node localization algorithms by PSO, BBO, Blended BBO, EBBO and immigration refusal have been presented in distributed and iterative fashion and experimented for node localization. This chapter has briefly outlined the algorithms and presented a summary of their results and comparison. In the ending average localization error is minimum in blended BBO as compared to other algorithms but time consumption is more.

CHAPTER 8

CONCLUSION AND FUTURE SCOPE

8.1 Introduction

The two objectives of this research can be summarized as:

Firstly, we investigate Wireless Sensor Networks in localization to localize unknown (target) nodes using PSO, BBO and its migration variants. Process of localization is implemented as it is most active research area in WSN. This is followed by localization in simulation environment. The goal of localization process is to determine actual position of nodes with minimum error.

Secondly, PSO is investigated with the objective for better localization in WSN. PSO is experimented in minimizing average localization error in many applications of WSN. Then BBO, Blended BBO, EBBO and immigration refusal are investigated for better localization. Both PSO, BBO and its migration variants algorithms are used for various transmitting ranges and anchor nodes to localize sensor nodes in wireless networks for their comparative performance in terms of number of nodes localized, localization accuracy and time consumption. Section 8. 2 presents the concluding remarks about what has been investigated, developed and contribute throughout this work. In Section 8. 3 future research agenda is discussed.

8.2 Conclusions

This work resulted in implemented process of localization using PSO, BBO and its migration variants for different ranges and anchor nodes in WSN. As, self organizing and fault tolerance characteristics of WSN make them promising for a number of military and civilian applications. Conclusion of this investigation study, as a whole are discussed as follows:

1. Here, PSO, BBO, Blended BBO, EBBO and Immigration refusal have been presented in distributed and iterative fashion and experimented for node localization. From Simulation results, it can be observed that proposed algorithms have better accuracy and fast convergence. A summary of results and comparison have been done in between proposed algorithms.

2. Average localization error is minimum in Blended BBO as compared to other algorithms in transmitting range=25, 20 and 15 respectively but time consumption is more i.e., 0.25217 for transmitting range=25, 0.2564 for transmitting range=20 and 0.3440 for transmitting range=15. As, the transmitting range decreases, less the number of nodes gets localized, more the average localization error but the time consumption is less as reported in [Satvir Singh, 2013b], [Singh et al., 2013], [Satvir Singh, 2013a] and as the number of anchor nodes increases more number of nodes gets localized with less average localization error but with more time consumption as reported in Chapter 7.

8.3 Future Research Agenda

Most of the times, a solution to a problem gives many issues to be investigated. The following remains on our future agenda

1. In this thesis, the optimization algorithms that are used for node localization in WSN are PSO, BBO, Blended BBO, EBBO and Immigration refusal for different transmitting range and anchor nodes, However PSO migrants or other optimization algorithms can be used for node localization in WSN.

2. Here, the node localization in WSN is done is Range-based localization. It can also done with Range-free localization algorithm.

3. We have used serial programming for better localization in WSN. For faster evoluation, parallel programming paradigm such as Computer Unified Device Architecture (CUDA) and OpenCL etc can be explored. CUDA and OpenCL is a scalable parallel programming model and software environment for parallel computing.

4. More BBO variants can be explored for better localization results in WSN.
5. Localization estimated by optimization algorithms can be done with different transmitting ranges and by varying number of anchor nodes.

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