INVESTIGATIONS ON LOCALIZATION OF BASE TRANSCEIVER STATION USING ARTIFICIAL BEE COLONY ALGORITHM

A Thesis

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, Kulvinder Kaur, hereby declare that the work presented in this thesis on INVESTIGATION ON LOCALIZATION OF BASE TRANSCEIVER STATION USING ARTIFICIAL BEE COLONY ALGORITHM 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 Master of Technology in Electronics and Communication Engineering.

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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 therein, however, approve the thesis only for the purpose for which it is submitted.

Dr. Satvir Singh [Supervisor]

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

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Sanjeev Dewra, Associate Proefessor & Head,
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Dedicated to

MY FAMILY

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THESIS OUTCOMES

International/National Journal Publications

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2. Kulvinder Kaur and Ankush Gawri, "Algorithms Based on Swarm Intelligence," *Emerging Principles and Practices in Computers and Communication Media (EPPCCM) 2012.*

ABSTRACT

This thesis is intended to present the investigations on swarm based optimization technique to find optimal Location of Base Transceiver Station (BTS) in a network. Swarm based Evolutionary Algorithms (EAs) are developed by modeling the behaviors of different swarms of animals and insects, e.g., ants, termites, bees, birds and fish, etc.

These EAs can be used to obtain near optimal solutions to NP-Hard real world problems one formulated as optimization problems. Artificial Bee Colony (ABC) algorithm is a meta-heuristic search algorithm and is investigated, in this thesis work, to localize BTS so as to cover maximum number of subscribers. This work, considered how to optimally determine the locations of BTS, such that minimum number of BTS can be installed to cover larger number of subscriber at lesser infrastructural cost.

Cellular wireless communication is facilitated by BTSs which have an appropriate spatial distribution. Cell planning is a fundamental and challenging part of cellular network design process. The automatic techniques that lend a helping hand to locate the optimal number of cell sites in a specified area are indispensable due to non-uniform user locations and traffic fluctuations. The goal of planning primarily focuses on selection of BTS sites to maximize coverage while considering numerous baseline issues, e.g., traffic demand to cover a specific region, availability of BTS sites, available channel capacity at each BTS and the service quality at various potential Traffic Demand Areas (TDAs). The exact size of the cells actually vary significantly due to several factors, including the topography of the land, anticipated number of calls in a particular area, number of obstacles, and traffic pattern of mobile users.

BTS is a piece of equipment that facilitates wireless communication between User Equipment (UE) and a network. UEs are devices, like mobile phones (handsets), WLL phones, computers

with wireless internet connectivity, WiFi and WiMAX devices and others. BTS works by regularly sending beacon signal in its coverage range, registration the mobile station in its coverage and as soon as the mobile station invokes service a free channel is assigned to it. Mobile Station sends its voice or data signal to BTS and BTS sends it to BSC and BSC sends it to MSC and MSC connects to the other side Mobile Station/PSTN phone/ or connects to Short Message Service Center (SMSC) if the service is for Short Message Service (SMS) or Serving GPRS Support Node (SGSN) for internet service. Thus BTS is the first contact for connection or release of a mobile service.

Since the introduction of ABC algorithm, was proposed by Karaboga for optimizing numerical problems in 2005. The algorithm simulates the intelligent foraging behavior of honey bee swarms. It is a very simple, robust and population based stochastic optimization algorithm. In [Karaboga and Basturk, 2007] Karaboga and Basturk have compared the performance of the ABC algorithm with those of other well-known modern heuristic algorithms such as Genetic Algorithm (GA), Differential Evolution (DE), Particle Swarm Optimization (PSO) on unconstrained problems. In this work, ABC algorithm is extended for solving optimization problems. A swarm of virtual bees is generated and started to move randomly in two dimensional search space. Bees interact when they find some target nectar and the solution of the problem is obtained from the intensity of these bee interactions.

During simulations, experiments are conducted in the MATLAB 2010b environment. Required coverage area 100×100 sq. units. Once the site coordinates are evolved, the next step is to calculate the path loss, received power and attenuation from particular BTS to a receiving bin (Mobile Station or subscriber). The received power, path loss and attenuation are main parameters of considerations during the process of optimization using ABC algorithm and results are then to be compared with traditional method of clustering, i.e., K-mean clustering.

Strategy parameters for the ABC algorithm are follows: colony size (number of bees) equal to 100, number of employed bess/ food patches as half of the colony size, number of iterations as 50 number of runs as 10. The simulation was carried out with the following BTS parameters settings: Transmit power 500 mW, Frequency 850 MHz, BTS antenna height hBTS is 20 m to 200 m and MS antenna height hMS is 1m to 10 m. No. of required BTSs = 3 and No. of MSs = 25.

This thesis is outlined as follow: Chapter 1 is devoted to introduction to thesis as a whole that covers introduction to research topic, motivation, methodologies, contributions, research findings and organization of thesis. State-of-the-art study of the historical research in detailed to clarify the background of honey bees based optimization algorithms and an extensive review of work on ABC algorithm is represented in Chapter 2. Chapter 3, is devoted to introduction to BTS and main parameters of considerations during the process of optimization. Chapter 4 is dedicated to study of ABC, algorithmic flow of ABC and traditional K-mean clustering algorithm. In Chapter 5, firstly, MATLAB software introduced to carry out simulation and analysis. Secondly, implementations flow of ABC in MATLAB along with Optimization Toolbox. Simulation results of ABC and K-mean clustering algorithm to optimize the BTS location, are represented in Chapter 6. Finally, conclusion and future scopes of this research are discussed in Chapter 7.

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ABBREVIATIONS

Abbreviations	Description
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
AI	Artificial Intelligence
BBO	Biogeography Based Optimization
CLPSO	Comprehensive Learning Particle Swarm Optimization
BTS	Base Transceiver Station
MS	Mobile Station
AN	Application Node
AN	Sensor Node
CI	Computational Intelligence
DE	Differential Evolution
EAs	Evolutionary Algorithms
EBBO	Enhanced Biogeography-Based Optimization
EMS-GA	Emperor Selective Genetic Algorithm
FBR	Front to Back Ratio
FDR-PSO	Fitness Distance Ratio Particle Swarm Optimization
GA	Genetic Algorithm
GDE	Generalized Differential Evolution
GPRS	General Packet Radio Service
HSI	Habitat Suitability Index

MBC	Meteor Burst Communication
MOEAs	Multi-Objective Evolutionary Algorithms
MOMs	Method of Moments
MS-MPYA	Multi-Sector Monopole Yagi-Uda Array
MSAT	Mobile Satellite
NEC	Numerical Electromagnetics Code
NP	Population Size
NSGA	Nondominated Sorting Genetic Algorithm
PAE	Power Added Efficiency
PSO	Particle Swarm Optimization
RF	Radio Frequency
SA	Simulated Annealing
SIV	Suitability Index Variable
SLL	Side Lobe Level
UHF	Ultra High Freqyency
VHF	Very High Frequency
VSWR	Voltage Standing Wave Ratio
WLAN	Wireless Local Area Network
UMTS	Universal Mobile Telecommunication System
WSN	Wireless Sensor Network

NOTATIONS

Symbols	Description
L_p	Path Loss
A	Attenuation
P_r	Power received
h_{BTS}	BTS antenna height
h_{MS}	MS antenna height
f	Frequency
F	Maximum Fitness
n	Number of Iterations
d	Distance
NP	Population Size
p_i	Probability
f_i	Fitness value

LIST OF FIGURES

LIST OF TABLES

CONTENTS

CHAPTER 1

INTRODUCTION

This thesis presents investigational studies in Artificial Bee Colony (ABC) algorithm and their use in Base Station Localization. This introductory chapter presents an overview of thesis. This include introduction to research topic, motivation, methodologies, contributions, research findings and organization of thesis.

1.1 Introduction

Cellular wireless communication is facilitated by BTSs which have an appropriate spatial distribution. Cell planning is a fundamental and challenging part of cellular network design process. The automatic techniques that lend a helping hand to locate the optimal number of cell sites in a specified area are indispensable due to non-uniform user locations and traffic fluctuations. The goal of planning primarily focuses on selection of BTS sites to maximize coverage while considering numerous baseline issues, e.g., traffic demand to cover a specific region, availability of BTS +sites, available channel capacity at each BTS and the service quality at various potential Traffic Demand Areas (TDAs). The exact size of the cells actually vary significantly due to several factors, including the topography of the land, anticipated number of calls in a particular area, number of obstacles, and traffic pattern of mobile users.

When the cellular concept was first proposed, BTS locations were usually selected according to a regular reuse pattern. With the growth of cellular technology, it is becoming increasingly important for any cellular operator to have a network which is not only better in terms of quality of service than its competitors but also is more profitable than the others. The cost involved in setting up a network and the quality of the service offered is directly proportional to the number of BTS installed, more BTS, more is the cost but better coverage at more infrastructural cost.

The placement of BTSs is a tedious job for network designers, the reason being the frequency channels become increasingly congested and propagation environments become more complex. Suboptimal placement of BTS will result in not only expensive deployment costs, but a reduction in spectrum efficiency due to interference which could be devastating to a service provider considering the cost of spectrum license. In order to cope with the need of rapid wireless systems deployment, significant research efforts have been put into develop advance wireless planning techniques over the past few years.

The problem considered in this thesis is to determine the optimal locations of BTSs to meet traffic demands. Optimal coverage with minimum number of BTSs is essentially a resource allocation/optimization problem. The received power, path loss and attenuation are main parameters of considerations during the optimization.

Artificial Bee Colony (ABC) algorithm , introduced by Karaboga in 2005 is a metaheuristic search algorithm for numerical optimization inspired from intelligent foraging behavior of honey bees and is investigated, in this thesis, to localize BTSs so as to cover maximum number of subscribers. The results are then compared with K-Mean clustering method. K-means is one of traditional unsupervised learning algorithms that are useful in solving clustering problems.

1.1.1 Base Transceiver Station

A base transceiver station (BTS) is a piece of equipment that facilitates wireless communication between user equipment (UE) and a network. UEs are devices like mobile phones (handsets), WLL phones, computers with wireless internet connectivity, WiFi and WiMAX devices and others.

BTS works by regularly sending beacon signal in its coverage range, registration the mobile station in its coverage and as soon as the mobile station invokes service a free channel is assigned to it. MS sends its voice or data signal to BTS and BTS sends it to BSC and BSC sends it to MSC and MSC connects to the other side Mobile Station/PSTN phone/ or connects to SMSC if the service is for SMS or SGSN for internet service. Thus BTS is the first contact for connection or release of a mobile service.

1.1.2 Network Planning

The factors that make BTS Planning a costly affair can be summed up as follows [Demirkol et al., 2004]: firstly, if cell planning stage extends longer, then the overall development cost of the project goes up due to time dependency of the work. Secondly, the cost of setting up a new BTS includes the cost of hiring/buying land, RF cables, shelter for equipment, antennas, power sources, and maintenance. Lastly, the invaluable time factor that is involved for a perfect plan.

1.1.3 Cell Pattern

In cellular communication, systems the area to be covered is divided into a number of smaller areas known as cells, with each cell being served by a fixed radio site, called BTS. The cells are drawn for convenience as hexagons. The edges of the hexagons represent the theoretical equal power boundaries between cells, assuming that every BTS radiates the same power, propagation is homogenous in every cell and all BTS are similarly sited in either the center or at one corner of every cell. However, the reality of the coverage pattern will be some what different and can be fully determine using propagation planning tools coupled with a detailed study of the service area and fields measurement.

1.1.4 Artificial Bee Colony

ABC algorithm, introduced by Karaboga in 2005 [Karaboga and Basturk, 2007], is a meta-heuristic algorithm for numerical optimization inspired from intelligent foraging behavior of honey bees. Honey bee swarm allocates tasks dynamically and adapts itself in response to changes in the environment in a collective intelligent manner. Population based Evolutionary Algorithms (EAs) are developed by modeling the behaviors of different swarms of animals and insects, e.g., ants, termites, bees, birds, fishes. These EAs can be used to obtain near optimal solutions for NP-Hard arbitrary optimization problems. Biological honey bees have many intelligent features, e.g., photographic memories, space-age sensory, navigation systems, group decision making process during selection of their new nest sites, queen and brood tending, storing, retrieving and distributing honey and pollen, communication and foraging etc [Karaboga and Basturk, 2007].

1.1.5 K-Means Clustering Algorithm

K-means is one of traditional unsupervised learning algorithms that are useful in solving clustering problems. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume K clusters) fixed apriori. The main idea is to define K centers, one for each cluster. These centers should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other [Likas et al., 2003].

1.2 Motivation

ABC algorithm, introduced by Karaboga in 2005 [Karaboga and Basturk, 2007], is a meta-heuristic algorithm for numerical optimization inspired from intelligent foraging behavior of honey bees and is investigated, in this thesis, to localize BTSs so as to cover maximum number of subscribers. The results are then compared with K-Mean clustering method. K-means is one of traditional unsupervised learning algorithms that are useful in solving clustering problems.

A base transceiver station (BTS) is a piece of equipment that facilitates wireless communication between user equipment (UE) and a network. UEs are devices like mobile phones (handsets), WLL phones, computers with wireless internet connectivity, WiFi and WiMAX devices and others.

1.3 Objectives

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

1. To conduct under literature survey on artificial bee colony algorithm.
2. To understand the concepts of BTS localization and their effective parameters like received power, path loss and attenuation.
3. To develop algorithm for ABC and K-Mean clustering to localize BTS in MATLAB simulation environment.
4. To conduct comparative analysis on received power, path loss and attenuation for ABC and K-Mean clustering algorithm.

1.4 Methodology

1. Literature survey will be conducted from e-journals like IEEE, Elsevier, Springer and other renown journals.
2. MATLAB programming environment will be studied and used for development of ABC and K-Mean clustering algorithm for localization of BTSs in simulation environment.
3. Comparative study will be conducted based on the available simulation results.

1.5 Contributions

The main contributions of this report are :

1. To study BTS localization planning for their performance parameters.
2. To create ABC algorithm on MATLAB to optimize various locations of BTS.
3. To create K-Mean clustering algorithm on MATLAB to optimize various locations of BTS.

1.6 Thesis Outline

After the brief introduction to M.Tech. thesis given in Chapter 1, detailed study of the historical research using ABC reported till date is represented in Chapter 2.

Chapter 3 devoted understanding of various BTS parameters of considerations during the process of optimization. Here, we discuss the received power, path loss and attenuation obtained during simulation results are also represented for better understanding.

Chapter 4 is dedicated to study of ABC and K-mean clustering algorithm, literature of ABC, ABC algorithms flow.

In Chapter 5, firstly, MATLAB software developed, for simulation and analysis. Secondly, implementation flow of ABC and K-Mean clustering algorithm along with MATLAB, a brief introduction to MATLAB environment also presented in this chapter.

Chapter 6 represents simulation results of optimization performance of ABC and K-Mean clustering algorithm for optimal locations of BTS. Best results in tabulated form are also represented in this chapter.

Lastly, conclusion and future scopes of this research are discussed in Chapter 7.

CHAPTER 2

LITERATURE SURVEY

The needed detailed of literature survey, to get preliminary knowledge and search scope of investigation, to design algorithms for optimization problems is explained in this chapter. Contributions of researches are explained in detailed to clarify the background of honey bees based optimization algorithms, BTS related work and use of K-Mean clustering algorithm in this section and an extensive review of work on artificial bee algorithms is given in this chapter.

2.1 Introduction

A branch of nature inspired algorithms which are known as swarm intelligence is focused on insect behaviour in order to develop some meta-heuristics which can mimic insect's problem solution abilities. Ant colony optimization, particle swarm optimization, wasp nets etc. are some of the well known algorithms that mimic insect behaviour in problem modelling and solution. Artificial Bee Colony (ABC) is a relatively new member of swarm intelligence. ABC tries to model natural behaviour of real honey bees in food foraging. Honey bees use several mechanisms like waggle dance to optimally locate food sources and to search new ones. This makes them a good candidate for developing new intelligent search algorithms [Baykasoglu et al., 2007]. In this chapter an extensive review of work on artificial bee algorithms is given.

Afterwards, development of an ABC algorithm for solving generalized assignment problem which is known as NP-hard problem is presented in detail along with some comparisons.

It is a well known fact that classical optimization techniques impose several limitations on solving mathematical programming and operational research models. This is mainly due to inherent solution mechanisms of these techniques. Solution strategies of classical optimization algorithms are generally depended on the type of objective and constraint functions (linear, non-linear etc.) and the type of variables used in the problem modelling (integer, real etc.). Their efficiency is also very much dependent on the size of the solution space, number of variables and constraints used in the problem modelling, and the structure of the solution space (convex, non-convex, etc.). They also do not offer general solution strategies that can be applied to problem formulations where, different type of variables, objective and constraint functions are used. For example, simplex algorithm can be used to solve models with linear objective and constraint functions; geometric programming can be used to solve non-linear models with a polynomial or signomial objective function etc [Baykasoglu et al., 2007]. However, most of the optimization problems require different types of variables, objective and constraint functions simultaneously in their formulation. Therefore, classic optimization procedures are generally not adequate or easy to use for their solution. Researchers have spent a great deal of effort in order to adapt many optimization problems to the classic optimization procedures. It is generally not easy to formulate a real life problem that suits a specific solution procedure. In order to achieve this, it is necessary to make some modifications and/or assumptions on the original problem parameters (rounding variables, softening constraints etc.). This certainly affects the solution quality. A new set of problem and model independent nature inspired heuristic optimization algorithms were proposed by researchers to overcome drawbacks of the classical optimization procedures. These techniques are efficient and flexible [Baykasoglu et al., 2007].

2.2 ABC and Its Application

In [Yonezawa and Kikuchi, 1996], Yonezawa and Kikuchi examine the foraging behaviour of honey bees and construct an algorithm to indicate the importance of group intelligence principals. The algorithm is simulated with one and three foraging bees and the computational simulation results showed that three foraging bees are faster than the system with one foraging bee at decision making process. They also indicate that the honey bees have an adaptive foraging behaviour at complex environment.

In [Seeley and Buhrman, 1999], Seeley and Buhrman investigated the nest site selection behaviour of honey bee colonies. The nest site selection process starts with several hundred scout bees that search for potential nest sites. The scouts then return to the cluster, report their findings by means of waggle dances, and decide the new nest site. The type of waggle dance depends on the quality of the site being advertised.

In [Seeley, 1995], the authors repeated the observations of Lindauer by taking advantage of modern video-recording and bee-labelling techniques on three honey bee colonies. Many of the results confirmed with the previous study and some of the results provided new and important insights. They pointed out that a colony's strategy of decision making is a weighted additive strategy which is the most accurate but most information demanding one. This strategy evaluates each alternative according to the relative attributes, gives weights to each attribute according to its importance, sums the weighted attributes for each alternative, and finally chooses the alternative whose total valuation is the highest. Similarly, the bee colony considers a dozen or more alternative nest sites, evaluates each alternative nest site with respect to at least six distinct attributes with different weightings e.g. cavity volume, entrance height, entrance area, entrance direction etc. Consequently, the bee colony uses this strategy by distributing among many bees both the task of evaluating the alternative sites and the task of identifying the best of these sites.

In [Schmickl et al., 2005], Schmickl evaluate the robustness of bees' foraging behaviour by using a multiagent simulation platform. They investigate how the time-pattern of environmental fluctuations affects the foraging strategy and the efficiency of the foraging. They conclude that the collective foraging strategy of a honeybee colony is robust and adaptive, and that its emergent features allow the colony to find optimal solutions.

In [Lemmens et al., 2006],Lemmens investigated whether pheromone-based navigational algorithms (inspired by biological ant colony behaviour) are outperformed by non-pheromone-based navigational algorithms (inspired by biological bee colony behaviour) in the task of foraging. The results of the experiments showed that (i) pheromone-based navigational algorithms use less time per iteration step in small-sized worlds, (ii) non-pheromone-based algorithms are significantly faster when finding and collecting food and use fewer time steps to complete the task, and (iii) with growing world sizes, the non-pheromone-based algorithm eventually outperforms pheromone-based algorithms on a time per time step measure. In spite of all these profits it is mentioned that non-pheromone-based algorithms are less adaptive than pheromone-based algorithms.

In [Sato and Hagiwara, 1997], Sato and Hagiwara proposed an improved genetic algorithm based on foraging behaviour of honey bees. In a honey bee colony, each bee looks for the feed individually. When a bee finds feed, then it notifies the information to the other many bees by dance and they engage in a job to carry the feed. When they finish the work, each bee tries to find new one individually again. Similarly in the proposed algorithm, named Bee System, global search is done first, and some chromosomes with pretty high fitness (superior chromosomes) are obtained using the simple genetic algorithm. Second, many chromosomes obtain the information of superior chromosomes by the concentrated crossover and they search intensively around there using multiple populations. In the conventional crossover each pair is made randomly, while in the concentrated crossover all of the chromosomes make pair with superior chromosome. Lastly, pseudo-simplex method is contributed to enhance the local search ability of the Bee System. If the solution found by one cycle is not satisfactory, the global search is repeated.

In [Karaboga, 2005], Karaboga analyzes the foraging behaviour of honey bee swarm and proposes a new algorithm simulating this behaviour for solving multi-dimensional and multi-modal optimization problems, called Artificial Bee Colony (ABC). The main steps of the algorithm are: 1) send the employed bees onto the food sources and determine their nectar amounts; 2) calculate the probability value of the sources with which they are preferred by the onlooker bees; 3) stop the exploitation process of the sources abandoned by the bees; 4) send the scouts into the search area for discovering new food sources, randomly; 5) memorize the best food source found so far. In the algorithm, an artificial bee colony consists of three groups of bees: employed bees, onlookers and scouts. Employed bees are associated with a particular food source which they are currently exploiting. They carry the information about this particular source and share this information with a certain probability by waggle dance. Unemployed bees seek a food source to exploit. There are two types of unemployed bees: scouts and onlookers. Scouts search the environment for new food sources without any guidance. Occasionally, the scouts can accidentally discover rich, entirely unknown food sources. On the other hand onlookers observe the waggle dance and so are placed on the food sources by using a probability based selection process. As the nectar amount of a food source increases, the probability value with which the food source is preferred by onlookers increases, too. In the ABC algorithm the first half of the colony consists of the employed bees and the second half includes the onlookers. For every food source, there is only one employed bee. Another issue that is considered in the algorithm is that the employed bee whose food source has been exhausted by the bees becomes a scout. In other words, if a solution representing a food source is not improved by a predetermined number of trials, then the food source is abandoned by its employed bee and the employed bee is converted to a scout. The algorithm is tested on three well known test functions. From the simulation results, it is concluded that the proposed algorithm can be used for solving uni-modal and multimodal numerical optimization problems.

In [Yang, 2005], Yang presents a virtual bee algorithm (VBA) which is effective on function optimization problems. The main steps of the algorithm are: 1) create an initial population of virtual bees where each bee is associated with a memory; 2) encode the optimization function into virtual food; 3) define the criterion for communicating food location with others; 4) march all the virtual bees randomly to new positions for virtual food searching, find food and communicate with neighbouring bees by virtual waggle dance; 5) evaluate the encoded intensity /locations of bees; 6) decode the results to obtain the solution to the problem. However the proposed algorithm is similar with genetic algorithm, it is much more efficient due to the parallelism of the multiple independent bees. To realize this statement, the VBA algorithm is tested on two functions with two parameters, one is singlepeaked and the other is multi-peaked. The results show that the new algorithm is much efficient than genetic algorithm.

In [Karaboga and Basturk, 2007], Basturk and Karaboga presented another ABC algorithm and expanded the experimental results of Karaboga (2005). The performance of the algorithm is tested on five multi-dimensional benchmark functions and the results were compared with genetic algorithms. It is pointed out that ABC algorithm outperforms genetic algorithm for functions having multi-modality and uni-modality.

In [Pham et al., 2006a], Pham proposed an optimization algorithm inspired by the natural foraging behaviour of honey bees, called Bees Algorithm. The proposed algorithm is also applicable to both combinatorial and functional optimization problems. In real life, foraging process begins by scout bees being sent to search for promising flower patches. When they return to the hive, unload their nectar and go to the dance floor to perform a dance known as the waggle dance which is essential for colony communication. After waggle dancing, the dancer goes back to the flower patch with follower bees that were waiting inside the hive. More follower bees are sent to more promising patches. This allows the colony to gather food quickly and efficiently. Similarly Bees Algorithm starts with scout bees being placed randomly on the search space. The main steps of the algorithm are: 1) initialize population with random solutions; 2) evaluate fitness of the population; 3) determine a certain number of fittest bees and select their sites for neighbourhood search; 4) recruit a certain number of bees for selected sites, evaluate their fitness; 5) select the fittest bee from each site to form the new population; 6) assign remaining bees to search randomly and evaluate their fitness. The Bees Algorithm is applied to two standard functional optimization problems with two and six dimensions, respectively. The results showed that the Bees Algorithm is able to find solutions very close to the optimum. The algorithm is also applied to eight benchmark functions and the results were compared with deterministic simplex method, stochastic simulated annealing optimization procedure, genetic algorithm and ant colony system. Bees Algorithm generally outperformed other techniques in terms of speed of optimization and accuracy of results. On the other hand Bees Algorithm has too many tuneable parameters.

In [Lucic and Teodorovic, 2001], Luck and Teodorovic published the first study on Bee System based on the PhD thesis of Luck for 6 Travelling Salesman Problem (TSP) test problems. Luck (2002) aimed to explore the possible applications of collective bee intelligence in solving complex traffic and transportation engineering problems. In this context, (TSP) and stochastic vehicle routing problem (SVRP) were studied. TSP is an NP-hard problem that aims to find the minimum distance circuit passing through each node only once. The algorithm starts with locating the hive in one of the nodes on the graph that the bees are collecting nectar i.e. the graph in which the travelling salesman route should be discovered. The artificial bees collect the nectar during a certain prescribed time interval and the position of the hive is randomly changed. The bees start to collect the nectar from the new location and again the location of the hive is randomly changed. The iteration in the searching process represents one change of the hive's position and the iteration ends when one or more feasible solution is created. The artificial bees live in an environment characterized by discrete time and consequently each iteration is composed of a certain number of stages. During any stage, bees choose nodes to be visited in a random manner. By this probability function it is provided that the greater the distance between two nodes, the lower the probability that a bee chooses this link. The influence of the distance is lower at the beginning of the search process. The greater the number of iterations, the higher the influence of the distance. On the other hand the greater the total number of bees that visited by certain link in the past, the higher the probability is of choosing that link in the future. This represents the interaction between individual bees in the colony. During one stage the bee visits a certain number of nodes, create a partial travelling salesman tour, and return to the hive. In the hive the bee participates in a decision making process. The bee decides whether to recruit the nest mates by dancing before returning to the food source, to continue to forage at the food source without recruiting the nest mates, or to abandon the food source. The second alternative has very low probability since bees are social insects and communicate each other.

In [Lucic and Teodorovic, 2002], the procedure and the results were presented at [Lučić and Teodorović, 2003] Luck and Teodorovic (2003b). Luck and Teodorovic (2002, 2003a) [Lucic and Teodorovic, 2003]published their second and third study on Bee System based on Luck's (2002) 8 and 10 TSP test problems.

Luck and Teodorovic (2003b) combined Bee System algorithm, which was first proposed by Luck and Teodorovic (2001), and fuzzy logic approach to obtain good solutions for stochastic

VRP[Lucic and Teodorovic, 2003]. The proposed approach contains two steps: 1) solve VRP as a TSP by using Bee System and obtain frequently an infeasible solution to the original problem; 2) decide when to finish one vehicle's route and when to start with the next vehicle's route by using the solution created at the previous step and fuzzy rule base generated by Wang-Mendel's algorithm. Stochastic VRP is to find a set of routes that would minimize transportation cost where the locations of the depot, nodes to be served and vehicle capacity are known, and demand at the nodes only approximated. Due to the uncertainty of demand at the nodes, a vehicle might not be able to service a node once it arrives there due to insufficient capacity. It is assumed in such situations that the vehicle returns to the depot, empties what it has picked up thus far, returns to the node where it had a failure, and continues service along the rest of the planned route. Consequently, demand at nodes is treated as a random variable and actual demand value is known only after the visit to the node. The developed model was tested on 10 TSP examples. In order to convert the original TSP problems into the corresponding VRPs, the first node was treated as a depot. The results were compared with the best solution obtained by the heuristic algorithm based on Bee System. The results were found to be very close to the best solution assuming that the future node demand pattern was known.

In [Teodorović and DellOrco, 2005], Teodorovic and Dell'Orco proposed Bee Colony Optimization (BCO) meta-heuristic which was the generalization of the Bee System presented by Luck (2002). The BCO was capable to solve deterministic combinatorial problems, as well as combinatorial problems characterized by uncertainty. The primary goal of their paper was to explore the possible applications of collective bee intelligence in solving combinatorial problems characterized by uncertainty. In this respect Fuzzy Bee System (FBS) was introduced where the agents use approximate reasoning and rules of fuzzy logic in their communication and acting. The performance of FBS algorithm was tested on ride-matching problem which aims to constitute routing and scheduling of the vehicles and passengers by minimizing the total distance travelled by all participants, minimizing the total delay, or equalizing vehicle utilization. There were no theoretical results that could support proposed approach but preliminary results were very promising.

In [Nakrani and Tovey, 2003], Nakrani and Tovey proposed a honey bee algorithm for dynamic allocation of internet services. In the proposed algorithm, servers and HTTP request queues in an Internet server colony were modelled as foraging bees and flower patches respectively. The algorithm was compared with an omniscient algorithm that computes an optimal allocation policy, a greedy algorithm that uses past history to compute allocation policy, and an optimal-static algorithm that computes omnisciently the best among all possible static allocation policies. The experimental results showed that the algorithm performs better than static or greedy algorithms. On the other hand it was outperformed by greedy algorithm for some low variability access patterns.

In [Wedde et al., 2004a], Wedde introduced a fault-tolerant, adaptive and robust routing protocol inspired from dance language and foraging behaviour of honey bees for routing in telecommunication network, called BeeHive. In order to evaluate the performance of the algorithm, it was tested on Japanese Internet Backbone and compared with AntNet, DGA and OSPF. The results showed that BeeHive achieves a similar or better performance as compared to the other algorithms.

In [Wedde et al., 2004b], Bianco presented a mapping paradigm for large scale precise navigation that takes inspiration from the bees' large scale navigation behaviour. Bees performed very long navigations when they feed, travelling for many kilometres but, at the same time, getting an excellent precision when they return to their small hives. Test results demonstrated that such capabilities were sufficient to get rather good precision.

In [Chang, 2006a], Chong presented a novel approach that uses the honey bees foraging model, inspired by Nakrani and Tovey , to solve the job shop scheduling problem. Job shop scheduling is concerned with finding a sequential allocation of competing resources that optimizes a particular objective function. Each machine can process only one job and each job can be processed by only one machine at a time. The performance of the algorithm was tested on 82 job shop problem instances and compared with ant colony and tabu search algorithms. The experimental results conducted that tabu search outperforms other two heuristics according to solution quality and execution time. On the other hand bee algorithm performed slightly better than ant algorithm and the execution time for both heuristics was approximately equal.

In [Drias et al., 2005],Drias introduced a new intelligent approach named Bees Swarm Optimization (BSO), which is inspired from the behaviour of real bees especially harvesting the nectar of the easiest sources of access while always privileging the richest. The proposed algorithm was adapted to the maximum weighted satisfiability problem (MAX-W-SAT) problem which was NP-Complete. MAX-W-SAT problem asks for the maximum weight which can be satisfied by any assignment, given a set of weighted clauses. The performance of the algorithm was compared with GRASP, SSAT and AGO and it was concluded that BSO outperformed the other evolutionary algorithms.

In [Pham et al., 2006c], Pham presented the use of the Bees Algorithm, proposed by Pham et al. (2006a) to train the Learning Vector Quantization (LVQ) neural network for control chart pattern recognition. The training of a LVQ network can be regarded as the minimization of an error function. The error function defines the total difference between the actual output and the desired output of the network over a set of training patterns. In terms of the Bees Algorithm, each bee represents a LVQ network with a particular set of reference vectors. The aim of the algorithm was to find the bee with the set of reference vectors producing the smallest value of the error function. Despite the high dimensionality of the problem, the algorithm still succeeded to train more accurate classifiers than that produced by the standard LVQ training algorithm.

In [Pham et al., 2006b], Pham presented the use of the Bees Algorithm, proposed by Pham et al. (2006a) to train the Multi-layered Perceptron (MLP) neural network for control chart pattern recognition. The training of a MLP network can be regarded as the minimization of an error function. The error function defines the total difference between the actual output and the desired output of the network over a set of training patterns. In terms of the Bees Algorithm, each bee represents a MLP network with a particular set of weight vectors. The aim of the algorithm was to find the bee with the set of weight vectors producing the smallest value of the error function. Despite the high dimensionality of the problem, the algorithm succeeded to train more accurate classifiers than back propagation algorithm.

In [Pham et al., 2006d], Pham presented an application of the Bees Algorithm, proposed by Pham et al. (2006a) to the optimization of neural networks for the identification of defects in wood veneer sheets. The Bees Algorithm was used instead of a back propagation algorithm to optimize the weights of the neural network. The optimization using the Bees Algorithm involves the bees searching for the optimal values of the weights assigned to the connections between the neurons within the network where each bee represents a neural network with a particular set of weights. The aim of the Bees Algorithm was to find the bee producing the smallest value of the error function. The experimental results show that the Bees Algorithm was able to achieve an accuracy that was comparable to the back propagation method. However, the Bees Algorithm proved to be considerably faster.

In [Quijano and Passino, 2007], Quijano and Passino developed an algorithm, based on the foraging behaviour of honey bees, to solve resource allocation problem. The primary sources for constructing components of the proposed model were: dance strength determination, dance threshold, unloading area, dance floor and recruitment rates, explorer allocation and its relation to recruitment. They also proposed an engineering application on dynamic resource allocation for multi-zone temperature control, to highlight the main features of the dynamical operation of the honey bee social foraging algorithm.

In [Abbass, 2001a], Abbass presented the first novel search algorithm inspired by the marriage process in honey bees. A honey bee colony consists of the queen(s), drones, worker(s), and broods. In this study the colony was assumed to have a single queen and a single worker. In real life a mating flight starts with a dance performed by the queens and the drones follow the queens to mate with them. In each mating, sperm reaches the spermatheca and accumulates there to form the genetic pool of the colony.

In [Abbass, 2001c], Abbass presented a variation of the MBO algorithm which was first proposed by Abbass in [Abbass, 2001a] where the colony contains a single queen with multiple workers. For the workers six different heuristics were used: GSAT, random walk, random flip, random new, 1-point and 2-point crossover. The algorithm was tested on a group of one-hundred hard 3- SAT problems. The best results were occurred with the smallest colony size and average spermatheca size. On the other hand, the fittest worker was GSAT, which was followed by random walk. It was also showed that MBO performed better than GSAT alone although GSAT was the heuristic with the highest fitness in MBO.

In Abbass (2001c) analyzed the marriage behaviour of honey bees again as the continuation of the work in [Abbass, 2001c]. The difference between these studies was the number of queens and workers. In [Abbass, 2001b], considered the honey bee colony with more than one queen in addition to a group of workers, where at the colony of Abbass (2001a) there was only one queen and one worker. In the paper MBO algorithm was applied to fifty different 3-SAT problems containing 50 variables and 215 constraints. The experimental results concluded that the largest spermatheca size, an average colony size, and the smallest number of queens gave the best performance. On the other hand the algorithm was compared with WalkSAT, one of the state-of-the-art algorithms for SAT, and MBO algorithm outperformed WalkSAT.

In [Teo and Abbass, 2001], Teo and Abbass presented a modification of MBO algorithm which can be considered as an extension of Abbass (2001a) and Abbass (2001c). The purpose of this modification was to use a more conventional annealing approach during the trajectory acceptance decision to guide the search process towards a more optimal solution space. New trajectories were only be accepted as a potential drone for mating if it was a more optimal trajectory that was if the trajectory was fitter than the queen's genotype. Otherwise, if it was a trajectory that takes the search to a less optimal solution space, then it is only accepted probabilistically subject to the new annealing function. In other words, rather than accepting all the trajectories created during a queen's flight as in the original MBO algorithm, a new trajectory is accepted only if it is a move to a fitter solution space. Otherwise, the algorithm will accept a transition to a less optimal solution space probabilistically according to a function of the queen's fitness. On the other hand, five different heuristics were used for improving broods by workers: GSAT, random walk, probabilistic greedy, one point crossover, and WalkSAT.

As in [Abbass, 2001c] Teo and Abbass again considered the honey bee colony with only one queen. Experimental studies were conducted in three manner: testing each of five different heuristics working alone without MBO, testing the performance of each heuristic with the original MBO and modified MBO, and lastly testing the proposed algorithm against the original MBO using the five different heuristics operating in combination as a committee of heuristics. For the test problems, ten different 3-SAT problems were generated each comprising of 1075 constraints and 250 variables. The heuristic performance's resulted with the following order for the first group of experiments: WalkSAT, GSAT, random walk, probabilistic greedy and one point crossover. At the second group of experiments both the original and proposed annealing functions used during the mating flight process were similarly efficient with all heuristics. However, the effectiveness of MBO with WalkSAT in finding solutions was improved slightly by the new annealing function as the proposed version of MBO found more solutions than the original version. Lastly at the third group of experiments both annealing strategies were again similarly efficient. In [Teo and Hussein, 2003], Teo and Abbass proposed another modification of MBO algorithm based on Teo and Abbass in [Abbass, 2001a].

In both [Abbass, 2001c] and [Abbass, 2001a], the annealing function used the queen's fitness as the basis for accepting/rejecting a transition in the drone's space, either during the spawning or mating stage. In a conventional simulated annealing approach, the previous state was used as the basis for the transition. Moreover, from a biological point of view, the drone's creation is independent of the queen as they usually come from another colony, although they might be related. Therefore, it is more natural to accept a transition based on the drone's own fitness. As a result the objective of their paper was to test a purely conventional annealing approach as the basis for determining the pool of drones. The performance of the modified algorithm was tested on ten different 3-SAT problems and compared with the previous versions of MBO. All heuristics were failed to find even a single solution when working alone whereas their performances were improved significantly when combined with MBO. On the other hand the proposed version of MBO dominated the previous studies and able to find solutions for problems where the previous versions cannot.

In [Haddad et al., 2006a], Bozorg Haddad and Afshar benefited from MBO algorithm based on the study of Abbass (2001c) and performed an application to water resources management problems. The algorithm was modelled to find good solutions for optimum management of a single reservoir. The results compared very well with similar heuristic methods as well as global optimal results.

In [Haddad et al., 2006b], Bozorg Haddad proposed Honey-Bees Mating Optimization (HBMO) algorithm, based on Abbass (2001a, 2001c), to solve highly non-linear constrained and unconstrained real valued mathematical models. The performance of the HBMO was tested on several results obtained by genetic algorithm. Results from the genetic algorithm and HBMO algorithm converge well with minor improvement in the HBMO solution. Moreover, to illustrate the model application and performance, the HBMO algorithm was also used for developing an optimum operation policy for a single reservoir. The HBMO again generated a significantly better solution.

In [Afshar et al., 2007a], Afshar and Bozorg Haddad presented the honey-bee mating optimization (HBMO) algorithm and tested with a nonlinear, continuous constrained problem with continuous decision and state variables to demonstrate the efficiency of the algorithm in handling the single reservoir operation optimization problems. It is shown that the performance of the model is quite comparable with the results of the well-developed traditional linear programming (LP) solvers such as LINGO 8.0. Results obtained are quite promising and compare well with the final results of the other approach.

In [Chang, 2006b], Chang gave the first demonstration of the capability of the MBO approach in a theoretical perspective for solving combinatorial optimization problems and stochastic sequential decision making problems. The paper first concerned with MBO algorithm for solving non-stochastic combinatorial optimization problems and proved that MBO has the ability to converge to the global optimum value. MBO was then adapted into an algorithm called "Honey-Bees Policy Iteration" (HBPI) for solving infinite horizon discounted costs stochastic dynamic programming (SDP) problems, also known as markov decision processes (MDPs) and HBPI algorithm was also proved converging to the optimal value.

In [Chang, 2006a], Chang points out that MBO can be considered as a hybrid scheme of simulated annealing and genetic algorithm. Simulated annealing corresponds to the queen's mating flight to obtain the potential drone sperms in her spermatheca and genetic algorithm corresponds to broods generation and improvements step with some differences.

In [Afshar et al., 2007b], Afshar presented an improved version of the HBMO algorithm for continuous optimization problems and its application to a nonlinear-constrained continuous single reservoir problem. By the comparison with global optimum values obtained from LINGO 8.0 NLP solver, it was observed that the convergence of the algorithm to the optimum was very rapid.

In [Fathian et al., 2007], Fathian presented an application of HBMO algorithm for clustering which is one of the attractive data mining techniques that is in use in many fields. To evaluate the performance of the algorithm in clustering, it was tested on several real datasets and compared with several typical stochastic algorithms including the ACO algorithm, the simulated annealing approach, the genetic algorithms, and the tabu search approach. The results illustrated that the proposed HBMO approach can be considered as a viable and an efficient heuristic to find optimal or near optimal solutions to clustering problems since the results were very encouraging in terms of the quality of solutions found, the average number of function evaluations and the processing time required.

In [Horng, 2010], Horng, Ming-Huwia presented new multilevel MET algorithm based on the technology of the honey bee mating optimization (HBMO) is proposed. This proposed method is called the maximum entropy based honey bee mating optimization thresholding (MEHBMOT) method. Three different methods such as the particle swarm optimization (PSO), the hybrid cooperative-comprehensive learning based PSO algorithm (HCOCLPSO) and the Fast Otsus method are also implemented for comparison with the results of the proposed method. The experimental results manifest that the proposed MEHBMOT algorithm can search for multiple thresholds which are very close to the optimal ones examined by the exhaustive search method. In comparison with the other three thresholding methods, the segmentation results using the MEHBMOT algorithm is the best and its computation time is relatively low. Furthermore, the convergence of the MEHBMOT algorithm can rapidly achieve and the results validate that the proposed MEHBMOT algorithm is efficient.

In [Koudil et al., 2007], Koudil adapted MBO algorithm which was first presented by Abbass (2001) to solve integrated partitioning/scheduling problem in codesign. The proposed approach was tested on a benchmark problem and the results were compared with genetic algorithm. The test results showed that MBO achieves good results in terms of solution quality, and it gives better results than genetic algorithm in terms of execution times.

In [Benatchba et al., 2005], Benatchba used the MBO algorithm which was first presented by Abbass (2001a, 2001b, 2001c) to solve a data mining problem expressed as a Max-Sat problem. For MBO, four different heuristics were used for improving broods by workers: a local search algorithm LS, GSAT, HSAT, and GWSAT. The training set used as benchmark was extracted from a medical one, aiming at analyzing the most revealing symptoms of the presence or not of a laparotomy of the principal bile duct. The best result obtained with MBO was the solution with 96

In [Jung, 2003], Sung proposed queen-bee evolution to enhance the capability of genetic algorithms. In the queen-bee evolution algorithm the queen-bee crossbreeds with the other bees selected as parents by a different selection algorithm instead of known selection algorithms such as roulette wheel selection. This procedure increases the exploitation of genetic algorithms but on the other hand increases the probability of falling into premature convergence. To decrease this probability some individuals were strongly mutated instead of mutating all individuals with small mutation probability as in the normal evolution. The proposed algorithm was tested with one combinational and two typical function optimization problems. Experimental results demonstrated that the proposed algorithm enabled genetic algorithms to quickly approach to the global optimum.

In [Qin et al., 2004], Qin applied queen bee evolution which was proposed by Sung in [Jung, 2003] into economic power dispatch problem (EPD). EPD problem is to minimize the overall cost rate and meet the load demand of a power system simultaneously and formulated as a nonlinear constrained complex optimization problem. The numerical results demonstrated that the proposed algorithm was faster and more robust than the conventional genetic algorithm. Kara (2004) proposed a new crossover type, which is called Bee Crossover to improve the genetic algorithm's performance.

In [Azeem and Saad, 2004], Azeem and Saad proposed a modified queen bee evolution which was first presented by Sung [Jung, 2003]. In the proposed algorithm, if any solution has the fitness very close or above of the fitness of the queen bee, this solution is identified to a new pool as a queen bee where the original algorithm is limited to a single pool. Another difference between the original and proposed algorithm is on the crossover operator. The original algorithm utilizes uniform crossover where each gene is crossed with some probability. On the other hand proposed algorithm uses weighted uniform crossover where weights are assigned to each gene according to the similarity of the test patterns in the population. With this type of crossover, genetic algorithm will search more new state spaces. The algorithm was tested for tuning of scaling factor for the Fuzzy Knowledge Base Controller (FKBC) on two complex non-linear examples. Experiments showed that FKBC yielded superior results than conventional control algorithms in the complex situations where the system model or parameters were difficult to obtain. Moreover, the results were compared with roulettes wheel parent selection and obtained results were encouraging.

In [Pan et al., 2011], Pan, Quan-Ke and Fatih Tasgetirena proposed a discrete artificial bee colony (DABC) algorithm to solve the lot-streaming flow shop scheduling problem with the criterion of total weighted earliness and tardiness penalties under both the idling and no-idling cases. Unlike the original ABC algorithm, the proposed DABC algorithm represents a food source as a discrete job permutation and applies discrete operators to generate new neighboring food sources for the employed bees, onlookers and scouts. An efficient initialization scheme, which is based on the earliest due date (EDD), the smallest slack time on the last machine (LSL) and the smallest overall slack time (OSL) rules, is presented to construct the initial population with certain quality and diversity. In addition, a self adaptive strategy for generating neighboring food sources based on insert and swap operators is developed to enable the DABC algorithm to work on discrete/combinatorial spaces. Furthermore, a simple but effective local search approach is embedded in the proposed DABC algorithm to enhance the local intensification capability. Through the analysis of experimental results, the highly effective performance of the proposed DABC algorithm is shown against the best performing algorithms from the literature.

In the following sections of this work the application of a nature inspired bee based algorithm (that we name as Artificial Bee Colony, ABC)is used to optimally determine locations of Base Transceiver Station (BTS), such that minimum number of BTS can be installed to cover larger number of subscriber at lesser infrastructural cost.

2.3 Historical Developments in BTS Localization

In [Mathar and Niessen, 2000], Mathar proposed an optimum positioning of base stations for cellular radio networks. Finding optimum base station locations for a cellular radio network is considered as a mathematical optimization problem. Dependent on the channel assignment policy, the minimization of interferences or the number of blocked channels, respectively, may be more favourable. In this work, a variety of according analytical optimization problems are introduced. Each is formalized as an integer linear program, and in most cases optimum solutions can be given. Whenever by the complexity of the problem an exact solution is out of reach, simulated annealing is used as an approximate optimization technique. The performance of the different approaches is compared by extensive numerical tests.

In [Rose, 2001], Rose proposed a smart technique for determining base-station locations in an urban environment. With the increasing demand for cheaper and better wireless communication services from customers, and the tendency to move toward smaller cell sizes, it is becoming very important to optimally design the cell geometry and deploy the minimum number of base stations to provide maximum possible coverage and consider how to optimally determine the locations for the placement of base stations for a wireless system in an urban setting, given the cell coverage. An algorithm is presented that determines the optimal locations of the base stations without performing an exhaustive search. Using this algorithm, a 20-25% decrease in the number of base stations required has been observed for simulated environments. The computational complexity of the proposed algorithm is also discussed.

In [Vesterstrom and Riget, 2002], Vesterstrom proposed a positioning of Base Stations in Wireless Sensor Networks. This article, highlight the potential of careful positioning of the base station (BS), which acts as a sink node for the collected data, as a viable means for increasing the dependability of WSN. Categorize published work on optimal positioning of BS in WSN. Referring to such work as static positioning, and further introduce dynamic schemes that reposition the BS during the network operation. This work show that dynamic BS positioning can be very effective in optimizing the network functional and non-functional performance objectives and in coping with dynamic changes in the environment and available network resources.

In [Younis et al., 2003], Younis proposed a base-station repositioning for optimized performance of sensor networks.This work investigate the potential of base-station repositioning for enhanced network performance and address issues related to when should the base-station be relocated, where it would be moved to and how to handle its motion without any effect on data traffic. The approach tracks the distance from the closest hops to the base-station and the traffic density through these hops. When a hop that forward high traffic is further than a threshold the base-station qualifies the impact of the relocation on the network performance and moves if the overhead is justified. The presented approach is validated in a simulated environment.

In [Amaldi et al., 2003], Amaldi proposed a planning UMTS base station location: optimization models with power control and algorithms. Classical coverage models, adopted for second-generation cellular systems, are not suited for planning Universal Mobile Telecommunication System (UMTS) base station (BS) location because they are only based on signal predictions and do not consider the traffic distribution, the signal quality requirements, and the power control (PC) mechanism. It propose discrete optimization models and algorithms aimed at supporting the decisions in the process of planning where to locate new BSs. These models consider the signal-to-interference ratio as quality measure and capture at different levels of detail the signal quality requirements and the specific PC mechanism of the wideband CDMA air interface. Given that these UMTS BS location models are nonpolynomial (NP)-hard, they propose two randomized greedy procedures and a tabu search algorithm for the uplink (mobile to BS) direction which is the most stringent one from the traffic point of view in the presence of balanced connections such as voice calls. The different models, which take into account installation costs, signal quality and traffic coverage, and the corresponding algorithms, are compared on families of small to large-size instances generated by using classical propagation models.

In [Bogdanov et al., 2004], Bogdanov proposed a power-aware base station positioning for sensor networks. The problem of positioning data collecting base stations in a sensor network. They show that in general, the choice of positions has a marked influence on the data rate, or equivalently, the power efficiency, of the network. In this model, which is partly motivated by an experimental environmental monitoring system, the optimum data rate for a fixed layout of base stations can be found by a maximum flow algorithm. Finding the optimum layout of base stations, however, turns out to be an NP-complete problem, even in the special case of homogeneous networks. This analysis of the optimum layout for the special case of the regular grid shows that all layouts that meet certain constraints are equally good. They also consider two classes of random graphs, chosen to model networks that might be realistically encountered, and empirically evaluate the performance of several base station positioning algorithms on instances of these classes. In comparison to manually choosing positions along the periphery of the network or randomly choosing them within the network, the algorithms tested find positions, which significantly improve the data rate and power efficiency of the network. In 2004 FUTA proposed a design and planning of a base transceiver station(BTS). Communication an important aspect of human life. As man continues daily life. The need to continually communicate, acquire and share information becomes more obvious. It then becomes important and necessary to be more information conscious not only in the content but as well as the speed of its transfer. This work centers on the design of a Base Transceiver Station Service for Federal University of Technology, Akure which could later be integrated into the community's existing communication) network in order to reduce communication problems and Improve information dissemination within the community. The whole work is generally involved topographical study of Federal University of Technology (FUTA), Akurc. community geographically survey, sport coordinates and height measurements. The results of these studies, and measurements were used to recommend suitable transmitting location and antenna height measurements were used to recommend suitable transmitting parameters such as radiated power. Antenna gain and operating frequencies with a view to recommending an appropriate base station system equipment specification. Similarly, antenna designed by hardware meddling and software simulation for the recommended radiation patterns was carried out. A tested at 1,800 MHz using band antenna system discovery software Antenna. Instrument 2.50 the designed antenna for the actual service band was simulated on WIN-NEC. Antenna analysis 1.0 and radiation characteristics generate and examined. The project is intended to help an R. F. designer with no GSM system. It provides to get up speed with GSM system. It provides the student with an introduction to mobile telephone communication and overview of GSM. It introduces the main system components, the network structure and basic terminology used. It also discusses the basic concepts of Wireless communication our interface including physical and logical channels. In address including physical and logical channels. It addresses air interface, base station system components, their functions features and requires specification.

In [Vass and Vidács, 2005], Vass proposed a positioning mobile base station to prolong wireless sensor network lifetime. Energy efficiency is a critical issue in designing sensor networks, as the nodes have limited battery power. In this paper they propose to move the BS so as to prolong the network lifetime. This work present three strategies for moving the BS: (1) minimizing the average transmission energy; (2) minimizing the maximum transmission energy; and (3) minimizing the maximum relative consumed energy for every active sensor. We examined the case, when the BS is on the optimal location in each round using the three strategies.

In [Akella et al., 2005] Akella, proposed a base station location and channel allocation in a cellular network with emergency coverage requirements. The location of base stations (BS) and the allocation of channels are of paramount importance for the performance of cellular radio networks. Also cellular service providers are now being driven by the goal to enhance performance, particularly as it relates to the receipt and transmission of emergency crash notification messages generated by automobile telematics systems. In this work, a Mixed Integer Programming (MIP) problem is proposed, which integrates into the same model the base station location problem, the frequency channel assignment problem and the emergency notification problem. The purpose of unifying these three problems in the same model is to treat the tradeoffs among them, providing a higher quality solution to the cellular system design. Some properties of the formulation are proposed that give us more insight into the problem structure. An instance generator is developed that randomly creates test problems. A few greedy heuristics are proposed to obtain quick solutions that turn out to be very good in some cases. To further improve the optimality gap, we develop a Lagrangean heuristic technique that builds on the solution obtained by the greedy heuristics. Finally, the performance of these methods is analyzed by extensive numerical tests and a sample case study is presented.

In [Pan et al., 2005], Pan proposed an optimal base-station locations in two-tiered wireless sensor networks. It considered generic two-tiered wireless sensor networks (WSNs) consisting of sensor clusters deployed around strategic locations, and base-stations (BSs) whose locations are relatively flexible. Within a sensor cluster, there are many small sensor nodes (SNs) that capture, encode, and transmit relevant information from a designated area, and there is at least one application node (AN) that receives raw data from these SNs, creates a comprehensive local-view, and forwards the composite bit-stream toward a BS. This paper focuses on the topology control process for ANs and BSs, which constitute the upper tier of two-tiered WSNs. Since heterogeneous ANs are battery-powered and energy-constrained, their node lifetime directly affects the network lifetime of WSNs. By proposing algorithmic approaches to locate BSs optimally, to maximize the topological network lifetime of WSNs deterministically, even when the initial energy provisioning for ANs is no longer always proportional to their average bit-stream rate. The obtained optimal BS locations are under different lifetime definitions according to the mission criticality of WSNs. By studying intrinsic properties of WSNs, they establish the upper and lower bounds of maximal topological lifetime, which enable a quick assessment of energy provisioning feasibility and topology control necessity. Numerical results are given to demonstrate the efficacy and optimality of the proposed topology control approaches designed for maximizing network lifetime of WSNs.

In [Ahmed et al., 2012a], Ahmed proposed a base stations locations optimization in an airport environment using genetic algorithms. Traditionally the locations of the base stations (BSs) in an indoor environment are optimised based on either traffic demand, signal to noise ratio (SNR), energy consumption or coverage area. However, considering only one of these parameters does not yield an optimum design, which is needed for efficient cost-effective planning with the required quality of service (QoS). Moreover, this problem becomes extremely challenging in highly dynamic environments such as airports, shopping malls and train stations where both spatial and temporal traffic variations are considerably high. Due to the continuous growth in international air traffic and the dynamic behaviour of passengers in an airport environment, providing reliable and cost-effective communication facilities to passengers and staff becomes even more difficult at different times and locations. Using data from Heathrow Terminal 4 (T4), we, in this paper, develop T4 passenger flow models which take both the spatial and temporal variations into account and help us accurately determine the traffic demand (TD), coverage area and path loss and thus outage and energy consumption. Moreover, we propose a multi-objective genetic algorithm (GA) which serves traffic demand and minimises both outage and energy consumption of the whole network. This eventually minimises the number of BSs while optimising their locations. The results reveal that only a few (i.e. 1-4) more base stations are required when we consider all three parameters together compared to the TD only. However our proposed GA, considering TD, outage and energy consumption, achieves lower outage and consumes almost 90% less transmission energy compared to the case of TD only while serving the same amount of traffic in such a dynamic environment.

In [Ahmed et al., 2012b], Ahmed proposed an energy-efficient base stations locations optimization in an airport environment. Optimizing the locations of base stations (BSs) is very challenging in highly dynamic environments such as airports, shopping malls and train stations where both spatial and temporal traffic variations are considerably high. Due to the continuous growth in international air traffic and the dynamic behaviour of passengers in an airport environment, providing reliable and cost effective communication facilities to passengers and staff becomes even more difficult at different times and locations. Using real measurements from Heathrow Terminal 4 (T4), we, in this paper, develop T4 passenger flow models which take both the spatial and temporal variations into account and help us accurately determine the traffic demand (TD), coverage area and path loss and thus outage and energy consumption. In this paper, we develop a multi-objective genetic algorithm (GA) which serves traffic demand and minimizes both outage and energy consumption of the whole network. This eventually minimizes the number of BSs while optimizing their locations. To validate GA's results, a multi-objective mixed integer linear programming (MILP) model has been developed and both are found to be in good agreement. The results also reveal that only a few more base stations are required when they consider all three parameters together compared to the TD only case. However multiparametric objective function, considering TD, outage and energy consumption, consumes 100 times less transmission energy compared to the case of TD only while serving the same amount of traffic in such a dynamic environment.

In [Dvorsky et al., 2012], Dvorsky proposed an improved GSM-based localization by incorporating secondary network characteristics. The techniques used in GSM networks for mobile station localization typically use several methods with different level of granularity, based on the base network parameters such as Cell Identification, Timing Advance, the position of Base Transceiver Station, the parameters of Base Transceiver Station antenna etc. This article introduces several others parameters that can be used for network description. This extension can be useful with visualization of localization outputs in cellular network.

In [Malik et al., 2012], Malik proposed a mobile node localization in cellular networks. Location information is the major component in location based applications. This information is used in different safety and service oriented applications to provide users with services according to their Geolocation. There are many approaches to locate mobile nodes in indoor and outdoor environments. In this work, they are interested in outdoor localization particularly in cellular networks of mobile nodes and presented a localization method based on cell and user location information. Localization method is based on hello message delay (sending and receiving time) and coordinate information of Base Transceiver Station (BTSs). To validate our method across cellular network,they implemented and simulated this method in two scenarios i.e. maintaining database of base stations in centralize and distributed system. Simulation results show the effectiveness of our approach and its implementation applicability in telecommunication systems.

2.4 K-Mean Clustering Related Work

The K-means algorithm is a popular data-clustering algorithm. However, one of its drawbacks is the requirement for the number of clusters, K, to be specified before the algorithm is applied. But The K-means clustering algorithm was recently recognized as one of the top ten data mining tools of the last fifty years.

In [Chen et al., 1998], Chen proposed adaptive K-mean clustering algorithm is capable of segmenting the regions of smoothly varying intensity distributions. Spatial constraints are incorporated in the clustering algorithm through the modeling of the regions by Gibbs random fields. Knowledge-based morphological operations are then applied to the segmented regions to identify the desired regions according to the a priori anatomical knowledge of the region-of-interest. This proposed technique has been successfully applied to a sequence of cardiac CT volumetric images to generate the volumes of left ventricle chambers at 16 consecutive temporal frames. Our final segmentation results compare favorably with the results obtained using manual outlining. Extensions of this approach to other applications can be readily made when a priori knowledge of a given object is available.

In [Bradley and Fayyad, 1998], Bradley demonstrate the application of this method to the popular K-Means clustering algorithm and show that refined initial starting points indeed lead to improved solutions. Refinement run time is considerably lower than the time required to cluster the full database. The method is scalable and can be coupled with a scalable clustering algorithm to address the large-scale clustering problems in data mining.

In [Krishna and Narasimha Murty, 1999], Krishna Genetic K-means algorithm. Krishna proposed a novel hybrid genetic algorithm (GA) that finds a globally optimal partition of a given data into a specified number of clusters. GA's used earlier in clustering employ either an expensive crossover operator to generate valid child chromosomes from parent chromosomes or a costly fitness function or both. To circumvent these expensive operations, it hybridize GA with a classical gradient descent algorithm used in clustering, viz. K-means algorithm.

Hence, the name genetic K-means algorithm (GKA). It define K-means operator, one-step of K-means algorithm, and use it in GKA as a search operator instead of crossover. It also define a biased mutation operator specific to clustering called distance-based-mutation. Using finite Markov chain theory, it prove that the GKA converges to the global optimum. It is observed in the simulations that GKA converges to the best known optimum corresponding to the given data in concurrence with the convergence result. It is also observed that GKA searches faster than some of the other evolutionary algorithms used for clustering.

In [Har-Peled and Kushal, 2005], Har-Peled proposed smaller coresets for k-median and k-means clustering.

In [Streichert et al., 2005], Streichert proposed a parallelization of multi-objective evolutionary algorithms using clustering algorithms. While single-objective Evolutionary Algorithms (EAs) parallelization schemes are both well established and easy to implement, this is not the case for Multi-Objective Evolutionary Algorithms (MOEAs). Nevertheless, the need for parallelizing MOEAs arises in many real-world applications, where fitness evaluations and the optimization process can be very time consuming. In test the divide and conquer approach to parallelize MOEAs, aimed at improving the speed of convergence beyond a parallel island MOEA with migration and suggest a clustering based parallelization scheme for MOEAs and compare it to several alternative MOEA parallelization schemes on multiple standard multi-objective test functions.

In [Ahmad and Dey, 2007], Ahmad proposed K-mean clustering algorithm for mixed numeric and categorical data. Use of traditional K-mean type algorithm is limited to numeric data. This work presents a clustering algorithm based on K-mean paradigm that works well for data with mixed numeric and categorical features. They propose new cost function and distance measure based on co-occurrence of values. The measures also take into account the significance of an attribute towards the clustering process. It present a modified description of cluster center to overcome the numeric data only limitation of k-mean algorithm and provide a better characterization of clusters. The performance of this algorithm has been studied on real world data sets. Comparisons with other clustering algorithms illustrate the effectiveness of this approach.

In [Deelers and Auwatanamongkol, 2007], Deelers proposed an algorithm to compute initial cluster centers for K-means clustering. Data in a cell is partitioned using a cutting plane that divides cell in two smaller cells. The plane is perpendicular to the data axis with the highest variance and is designed to reduce the sum squared errors of the two cells as much as possible, while at the same time keep the two cells far apart as possible. Cells are partitioned one at a time until the number of cells equals to the predefined number of clusters, K. The centers of the K cells become the initial cluster centers for K-means. The experimental results suggest that the proposed algorithm is effective, converge to better clustering results than those of the random initialization method. The research also indicated the proposed algorithm would greatly improve the likelihood of every cluster containing some data in it.

In [Ben-David et al., 2007], Ben-David proposed stability of K-Means Clustering. Clustering stability is a common heuristics used to determine the number of clusters in a wide variety of clustering applications. It continue the theoretical analysis of clustering stability by establishing a complete characterization of clustering stability in terms of the number of optimal solutions to the clustering optimization problem. The results complement earlier work of Ben-David, von Luxburg and Pl, by settling the main problem left open there. The analysis shows that, for probability distributions with finite support, the stability of K-means clusterings depends solely on the number of optimal solutions to the underlying optimization problem for the data distribution. These results challenge the common belief and practice that view stability as an indicator of the validity, or meaningfulness, of the choice of a clustering algorithm and number of clusters.

In [Hu and Su, 2008], Hu proposed a K-means clustering algorithm is a commonly used algorithm for palette design. If an adequate initial palette is selected, a good quality reconstructed image of a compressed colour image can be achieved. The major problem is that a great deal of computational cost is consumed. To accelerate the K-means clustering algorithm, two test conditions are employed in the proposed algorithm. From the experimental results, it is found that the proposed algorithm significantly cuts down the computational cost of the K-means clustering algorithm without incurring any extra distortion.

In [Lai et al., 2009], Lai proposed a fast K-means clustering algorithm using cluster center displacement. The computing time of proposed algorithm increases linearly with the data dimension d, whereas the computational complexity of major available kd-tree based algorithms increases exponentially with the value of d. Theoretical analysis shows that our method can reduce the computational complexity of full search by a factor of SF and SF is independent of vector dimension.

In [Sangalli et al., 2010], Sangalli proposed a problem of curve clustering when curves are misaligned is considered. A novel algorithm is described, which jointly clusters and aligns curves. The proposed procedure efficiently decouples amplitude and phase variability; in particular, it is able to detect amplitude clusters while simultaneously disclosing clustering structures in the phase, pointing out features that can neither be captured by simple curve clustering nor by simple curve alignment. The procedure is illustrated via simulation studies and applications to real data.

In [Oyelade et al., 2010], Oyelade proposed an application of K-means clustering algorithm for prediction of students academic performance. The ability to monitor the progress of students academic performance is a critical issue to the academic community of higher learning. A system for analyzing students results based on cluster analysis and uses standard statistical algorithms to arrange their scores data according to the level of their performance is described. It is also implemented K mean clustering algorithm for analyzing students result data. The model was combined with the deterministic model to analyze the students results of a private Institution in Nigeria which is a good benchmark to monitor the progression of academic performance of students in higher Institution for the purpose of making an effective decision by the academic planners.

2.5 Conclusion

D. Karaboga and his research group have been studying the ABC algorithm and its applications to real world problems. Karaboga and Basturk have investigated the performance of the ABC algorithm on unconstrained numerical optimization problems and its extended version for the constrained optimization problems and Karaboga applied ABC algorithm to neural network training. In 2010, Hadidi employed an Artificial Bee Colony (ABC) Algorithm based approach for structural optimization. In 2011, Zhang employed the ABC for optimal multi-level thresholding, MR brain image classification, cluster analysis, face pose estimation, and 2D protein folding.

ABC has other many application, such as Biological simulation, Continuous Optimization, Travelling Salesman Problem(TSP), TSP and Stochastic Vehicle Routing Problem, Stochastic Vehicle Routing, Ride-Matching Problem, Integrated Partitioning/Scheduling, Data Mining, Dynamic Allocation of Internet Service, Telecommunication Network Routing, Large Scale Precise Navigation, Water Resources Management Problems, Nonlinear constrained and unconstrained optimization, Economic Power Dispatch ,Genetic Algorithm Improvement etc. Historical developments in BTS localization and K-mean clustering related work also discussed in detailed in this chapter.

CHAPTER 3

BASE TRANSCEIVER STATION AND PARAMETERS

A base transceiver station (BTS) is a piece of equipment that facilitates wireless communication between user equipment (UE) and a network. UEs are devices like mobile phones (handsets), WLL phones, computers with wireless internet connectivity, WiFi and WiMAX devices and others.

3.1 Introduction to BTS

A base transceiver station (BTS) is a piece of equipment that facilitates wireless communication between user equipment (UE) and a network. UEs are devices like mobile phones (handsets), WLL phones, computers with wireless internet connectivity, WiFi and WiMAX devices and others. BTS works by regularly sending beacon signal in its coverage range, registration the mobile station in its coverage and as soon as the mobile station invokes service a free channel is assigned to it. MS sends its voice or data signal to BTS and BTS sends it to BSC and BSC sends it to MSC and MSC connects to the other side Mobile Station/PSTN phone/ or connects to SMSC if the service is for SMS or SGSN for internet service. Thus BTS is the first contact for connection or release of a mobile service. A BTS in general has the following parts:

1. **Transceiver**: Quite widely referred to as the driver receiver (DRX), DRX are either in the form of single (sTRU), double(dTRU) or a composite double radio unit (DRU). It basically does transmission and reception of signals. It also does sending and reception of signals to and from higher network entities (like the base station controller in mobile telephony).

2. **Power amplifier:** Amplifies the signal from DRX for transmission through antenna; may be integrated with DRX.

3. **Combiner:** Combines feeds from several DRXs so that they could be sent out through a single antenna. Allows for a reduction in the number of antenna used.

4. **Duplexer:** For separating sending and receiving signals to/from antenna. Does sending and receiving signals through the same antenna ports (cables to antenna).

5. **Antenna:** This is the structure that lies underneath the BTS; it can be installed as it is or disguised in some way (Concealed cell sites).

6. **Alarm extension system:** Collects working status alarms of various units in the BTS and extends them to operations and maintenance ($O\&M$) monitoring stations.

7. **control function:** Controls and manages the various units of BTS, including any software. On-the-spot configurations, status changes, software upgrades, etc. are done through the control function.

8. **Baseband receiver unit:** Frequency hopping, signal DSP, etc.

3.2 Parameters

The fitness of a solution is decided on the basis of three main parameters: (a) Power received, P_r, (b) Path loss, L_p, and (c) Attenuation, A, using (3.1), (3.2) and (3.3).

Path loss is determined based on three parameters. viz. (1) Transmit power P_t=500 mW (2) Frequency f=850 MHz and (3) BTS antenna height h_{BTS} = 20m to 200 m and (4) Mobile station antenna height h_{MS} = 1m to 10 m and d is distance between MS and BTS Hata [1980].

$$P_r = 10 \log_{10}(P_t) - abs(L_p) \tag{3.1}$$

$$L_p = 66.55 + (26.16)\log_{10} f - 13.82\log_{10} h_{BTS} - 3.2\log_{10} 11.75 h_{MS} \\ +44.9 - 6.55\log_{10} h_{BTS}\log_{10} d \qquad (3.2)$$

$$A = 42.6 + 20\log_{10} f + 26\log_{10} d \qquad (3.3)$$

Maximum fitness, F, is achieved given by equation (3.4).

$$F = \frac{1}{L_p A} abs(P_r) \qquad (3.4)$$

3.2.1 Path Loss Prediction Models

The most commonly used path loss models are:

(a) Okumura Model: Okumura developed an empirical model that is derived from extensive radio propagation studies in Tokyo. It is represented by means of curves with which is applicable for urban areas. For other terrain, Okumura has provided correction factors for three types of terrain:

1. Open Area: Corresponds to a rural, desert type of terrain.
2. Quasi Open area: Corresponds to rural, countryside kind of terrain.
3. Suburban area.

(b) Hata Model: The model is an empirical formulation of the graphical path loss data provided by Okumura. Hata presented the urban area propagation loss as a standard formula and supplied correction equations for other types of areas [Hata, 1980].

Path loss, L_p, is determined based on three parameters. viz. (1) Transmit power P_t=500 mW (2) Frequency f=850 MHz and (3) BTS antenna height h_{BTS} = 20m to 200 m and (4) Mobile station antenna height h_{MS} = 1m to 10 m and d is distance between MS and BTS [Hata, 1980] given in equation (3.5).

$$L_p = 66.55 + (26.16)\log_{10} f - 13.82\log_{10} h_{BTS} - 3.2\log_{10} 11.75h_{MS} \\ +44.9 - 6.55\log_{10} h_{BTS}\log_{10} d \quad (3.5)$$

3.3 Conclusion

This chapter, devoted understanding of various BTS parts and parameters of considerations during the process of optimization. Here, we discuss the received power, path loss and attenuation obtained during simulation. In this thesis, fitness maximization is be target in the coming chapters using ABC algorithms. The concept of ABC and algorithmic flow of ABC along with pseudo codes are discussed in the next chapter in detail.

CHAPTER 4

ABC AND K-MEAN CLUSTERING ALGORITHM

This chapter, dedicated to study of ABC and K-Mean clustering algorithm with the algorithmic flow.

4.1 Introduction

Swarm intelligence has become a research interest to many research scientists of related fields in recent years. Bonabeau has defined the swarm intelligence as any attempt to design algorithms or distributed problem-solving devices inspired by the collective behaviour of social insect colonies and other animal societies [Bonabeau et al., 1999]. Bonabeau et al. focused their viewpoint on social insects alone such as termites, bees, wasps as well as other different ant species. However, the term swarm is used in a general manner to refer to any restrained collection of interacting agents or individuals. The classical example of a swarm is bees swarming around their hive; nevertheless the metaphor can easily be extended to other systems with a similar architecture. An ant colony can be thought of as a swarm whose individual agents are ants. Similarly a flock of birds is a swarm of birds. An immune [De Castro and Von Zuben, 1999] system is a swarm of cells and molecules as well as a crowd is a swarm of people [**?**]. Particle Swarm Optimization (PSO) Algorithm models the social behaviour of bird flocking or fish schooling [Kennedy and Eberhart, 1995]. Two fundamental concepts, self-organization and division of labour, are necessary and sufficient properties to obtain swarm intelligent behaviour such as distributed problem solving systems that self-organize and adapt to the given environment.

FIGURE 4.1: Honey Bees

(a) Self-organization can be defined as a set of dynamical mechanisms, which result in structures at the global level of a system by means of interactions among its low-level components. These mechanisms establish basic rules for the interactions between the components of the system. The rules ensure that the interactions are executed on the basis of purely local information without any relation to the global pattern. Bonabeau et al. have characterized four basic properties on which self organization relies: Positive feedback, negative feedback, fluctuations and multiple interactions [Bonabeau et al., 1999]:

1 Positive feedback is a simple behavioral rules of thumb that promotes the creation of convenient structures. Recruitment and reinforcement such as trail laying and following in some ant species or dances in bees can be shown as the examples of positive feedback.

2 Negative feedback counterbalances positive feedback and helps to stabilize the collective pattern. In order to avoid the saturation which might occur in terms of available foragers, food source exhaustion, crowding or competition at the food sources, a negative feedback mechanism is needed.

3 Fluctuations such as random walks, errors, random task switching among swarm individuals are vital for creativity and innovation. Randomness is often crucial for emergent structures since it enables the discovery of new solutions.

4 In general, self organization requires a minimal density of mutually tolerant individuals, enabling them to make use of the results from their own activities as well as others.

(b) Inside a swarm, there are different tasks, which are performed simultaneously by specialized individuals. This kind of phenomenon is called division of labour. Simultaneous task performance by cooperating specialized individuals is believed to be more efficient than the sequential task performance by unspecialized individuals. Division of labour also enables the swarm to respond to changed conditions in the search space. Two fundamental concepts for the collective performance of a swarm presented above, self-organization and division of labour are necessary and sufficient properties to obtain swarm intelligent behaviour such as distributed problem-solving systems that self-organize and -adapt to the given environment [Karaboga, 2005].

4.2 Behaviour Of Honey Bee Swarm

Before presenting the algorithms described to use intelligent behaviors and their applications, behavior of the colony is explained below:

4.2.1 Queen Bee

Queen bee can live several years. She is the only egg-laying female who is the mother of all the members of the colony. The queen usually mates only once in her life and she fertilizes for two or more years by the sperms stored in the mating. After consuming the sperms, she produces unfertilized eggs and one of her daughters is selected as a queen in order to keep on egg-laying. A laid egg hatches into larva, pupate, adult bee, respectively. When the colony is lack of food sources, queen produces new eggs. If the colony becomes too crowded, the queen stops laying. A healthy queen bee can lay 2,000 eggs a day and 175,000200,000 eggs per year depending on the conditions mentioned [Karaboga, 2005].

4.2.2 Drones

Drones are the fathers of the colony, in other words drones are male bees. They are produced from unfertilized eggs, queens and workers produced from fertilized eggs which are fed differently as larvae. They never live more than 6 months. There are several hundred of drones in the colony in summer times. The primary task of a drone is to fertilize a new queen. Drones die after they mate with the queen.

4.2.3 Workers

They collect food, store it, remove debris and dead bees, ventilate the hive and guard the hive. Workers make the wax cells in which the queen lays eggs and feed the larvae, drones and queen by special substance or secretion of their salivary glands. The tasks of a worker bee are based on its age and the needs of the colony. In second half of her life, she works as a forager by initially leaving the hive for short fights in order to learn the location of the hive and the environment topology. They live for 6 weeks during summer times and 49 months during the winter times.

4.2.4 Mating-Flight

The queen mates during her mating flights far from the nest. A mating flight starts after a dance performed by the queen bee. During the flight the drones follow the queen and mate with her in the air. A drone mates with a queen probabilistically according to queens speed and fitness of the queen and the drone. Sperm of the drones will be deposited and accumulated in the queens spermatheca to form the genetic pool of the potential broods to be produced by the queen.

4.2.5 Foraging

Foraging is the most important task in the hive. Many studies (Von F the foraging behavior of each individual bee and what types of external information (such as odor, location information in the waggle dance, the presence of other bees at the source or between the hive and the source) and internal information (such as remembered source location or source odor) affect this foraging behavior. Foraging process starts with leaving the hive of a forager in order to search food source to gather nectar. After finding a flower for herself, the bee stores the nectar in her honey stomach. Based on the conditions such as richness of the flower and the distance of the flower to the hive, the bee fills her stomach in about 30120 min and honey making process begins with the secretion of an enzyme on the nectar in her stomach. After coming back to the hive, the bee unloads the nectar to empty honeycomb cells and some extra substances are added in order to avoid the fermentation and the bacterial attacks. Filled cells with the honey and enzymes are covered by wax

4.2.6 Dance

After unloading the nectar, the forager bee which has found a rich source performs special movements called dance on the area of the comb in order to share her information about the food source such as how plentiful it is, its direction and distance and recruits the other bees for exploiting that rich source. While dancing, other bees touch her with their antenna and learn the scent and the taste of the source she is exploiting. She dances on different areas of the comb in order to recruit more bees and goes on to collect nectar from her source. There are different dances performed by bees depending on the distance information of the source: round dance, waggle dance, and tremble dance. If the distance of the source to the hive is less than 100 meters, round dance is performed while the source is far away, waggle dance is performed. Round dance does not give direction information. Incase of waggle dance, direction of the source according to the sun is transferred to other bees. Longer distances cause quicker dances . The tremble dance is performed when the foraging bee perceives a long delay in unloading its nectar.

The minimal model of forage selection that leads to the emergence of collective intelligence of honey bee swarms consists of three essential components: food sources, employed foragers and unemployed foragers and the model defines two leading modes of the behaviour: the recruitment to a nectar source and the abandonment of a source.

(i) **Food Sources:** The value of a food source depends on many factors such as its proximity to the nest, its richness or concentration of its energy, and the ease of extracting this energy. For the sake of simplicity, the profitability of a food source can be represented with a single quantity.

(ii) **Employed Foragers:** They are associated with a particular food source which they are currently exploiting or are employed at. They carry with them information about this particular source, its distance and direction from the nest, the profitability of the source and share this information with a certain probability.

(iii) **Unemployed Foragers:** They are continually at look out for a food source to exploit. There are two types of unemployed foragers: scouts, searching the environment surrounding the nest for new food sources and onlookers waiting in the nest and establishing a food source through the information shared by employed foragers. The mean number of scouts averaged over conditions is about 5-10%. The exchange of information among bees is the most important occurrence in the formation of the collective knowledge. While examining the entire hive it is possible to distinguish between some parts that commonly exist in all hives. The most important part of the hive with respect to exchanging information is the dancing area. Communication among bees related to the quality of food sources takes place in the dancing area. This dance is called a waggle dance.

Since information about all the current rich sources is available to an onlooker on the dance floor, probably she can watch numerous dances and decides to employ herself at the most profitable source. There is a greater probability of onlookers choosing more profitable sources since more information is circulated about the more profitable sources. Employed foragers share their information with a probability proportional to the profitability of the food source, and the sharing of this information through waggle dancing is longer in duration. Hence, the recruitment is proportional to the profitability of the food source [Karaboga, 2005].

In the case of honey bees, the basic properties on which self organization relies are as follows:

(i) **Positive feedback**: As the nectar amount of food sources increases, the number of onlookers visiting them increases, too.

(ii) **Negative feedback**: The exploitation process of poor food sources is stopped by bees.

(iii) **Fluctuations:** The scouts carry out a random search process for discovering new food sources.

(iv) **Multiple interactions**: Bees share their information about food sources with their nest mates on the dance area.

4.3 Artificial Bee Colony Algorithm

ABC is one of the recently developed population based algorithms which has shown impressive performance over other Evolutionary Algorithms (EAs). ABC is a metaheuristic algorithm for numerical optimization inspired from intelligent foraging behavior of honey bees. ABC results presented by researchers are better than other optimization techniques like Ant Colony Optimization, Particle Swarm Optimization, Genetic Algorithm and Simulated Annealing [Karaboga and Basturk, 2007].

ABC algorithm uses a colony of artificial bees. The bees are classified into three types: 1. Employed bees, 2. Onlooker bees, and 3. Scout bees. Each employed bee is associated with a food source, which it exploits currently. A bee waiting in the hive to choose a food source is an onlooker bee. The employed bees share information about the food sources with onlooker bees in the dance area. A scout bee, on the other hand, carries out a random search to discover new food sources.

In a robust search process, exploration and exploitation must be carried out together. In the ABC algorithm, the scout bees are in charge of the exploration process, while the employed and onlooker bees carry out the exploitation process.

In the algorithm, one half of the population consists of employed bees and the other half consists of onlooker bees. The number of food sources equals the number of employed bees. During each cycle, the employed bees try to improve their food sources. Each onlooker bee then chooses a food source based on the nectar amount available at that food source. An employed bee whose food source is exhausted becomes a scout bee. The scout bee then searches for a new food source [Narasimhan, 2009].

The position of a food source represents a solution for an optimization problem. The nectar amount of the food source is the fitness of the solution. Each solution is represented using a D-dimensional vector. Here, D is the number of optimization parameters. Initially, SN solutions are generated randomly, where SN equals the number of employed bees. Let MCN be the maximum number of cycles that the algorithm would run. During each cycle, the employed and onlooker bees improve the solutions through a neighborhood search. A new solution v_i in the neighborhood of an existing solution x_i is produced as follows:

$$v_{ij} = x_{ij} + \Phi_{ij}(x_{ij} - x_{kj}) \tag{4.1}$$

where k=1, 2, ..., SN and Φ is a random number between [-1, 1] and j=1, 2,..., D. k and j are chosen randomly. A greedy selection is then performed between x_i and v_i.

The onlooker bees are placed on food sources using the roulette wheel selection method [**?**]. An onlooker bee thus chooses a food source at position x_i with a probability p_i calculated as follows:

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{4.2}$$

Here, fit_i is calculated using the following equation:

$$fit_i = \begin{cases} \frac{1}{1+fi} & \text{if } fi \leq 0 \\ 1 + abs(fi) & \text{if } fi \geq 0 \end{cases} \tag{4.3}$$

where f_i is the fitness value of the solution.

A solution representing a food source is abandoned by an employed bee if it cannot be improved for a predetermined number of trials given by the parameter limit. The employed bee then becomes a scout bee and randomly produces a new solution replacing the existing solution. The value of limit is generally chosen as SNxD.

Algorithm 1 ABC Algorithmic Flow

1: Generate the initial solutions (positions of food sources) randomly and evaluate them.

2: For each solution x_i, determine a neighbor v_i using (4.1) and perform a greedy selection between x_i and v_i.

3: Calculate the probabilities for the solutions using (4.2).

4: Use the roulette wheel selection method to place the onlookers on the food sources and improve the corresponding solutions (as in step 2).

5: Determine the abandoned solution (if any) and replace it with a new randomly produced solution.

6: Record the best solution obtained till now.

7: Repeat steps 2 to 6 until MCN cycles are completed.

4.4 Application to real-world problems

In 2005 D. Karaboga and his research group have been studying the ABC algorithm and its applications to real world problems. Karaboga and Basturk have investigated the performance of the ABC algorithm on unconstrained numerical optimization problems and its extended version for the constrained optimization problems and Karaboga applied ABC algorithm to neural network training. In 2010, Hadidi employed an Artificial Bee Colony (ABC) Algorithm based approach for structural optimization. In 2011, Zhang employed the ABC for optimal multi-level thresholding, MR brain image classification, cluster analysis, face pose estimation, and 2D protein folding.

ABC has other many application, such as Biological simulation, Continuous Optimization, Travelling Salesman Problem(TSP), TSP and Stochastic Vehicle Routing Problem, Stochastic Vehicle Routing, Ride-Matching Problem, Integrated Partitioning/Scheduling, Data Mining, Dynamic Allocation of Internet Service, Telecommunication Network Routing, Large Scale Precise Navigation, Water Resources Management Problems, Nonlinear constrained and unconstrained optimization, Economic Power Dispatch ,Genetic Algorithm Improvement etc.

4.5 K-Means Clustering Algorithm

K-means is one of traditional unsupervised learning algorithms that are useful in solving clustering problems. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume K clusters) fixed apriori. The main idea is to define K centers, one for each cluster. These centers should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other [Likas et al., 2003]. The next step is to take each point belonging to a given data set and associate it to the nearest center. When no point is pending, the first step is completed and an early group age is done. At this point we need to re-calculate K new centroids as barycenter of the clusters resulting from the previous step. These K new centroids, a new binding has to be done between the same data set points and the nearest new center. A loop has been generated. As a result of this loop may notice that the K centers change their location step by step until no more changes are done or in other words centers do not move any more. Finally, this algorithm aims at minimizing an objective function know as squared error function given by (4.4)

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} (\|x_i - v_j\|)^2 \tag{4.4}$$

where $\|x_i - v_j\|$ is the Euclidean distance between x_i and v_j. $'c_i'$ is the number of data points in i^{th} cluster. $'c'$ is the number of cluster centers [**?**].

The basic step of K-means clustering is simple. In the beginning, number of cluster K are determined and assume the centroid or center of these clusters. Take any random objects as the initial centroids or the first K objects can also serve as the initial centroids. If the number of data is less than the number of cluster then assign each data as the centroid of the cluster. Each centroid will have a cluster number. If the number of data is bigger than the number of cluster, for each data, calculate the distance to all centroid and get the minimum distance. This data is said belong to the cluster that has minimum distance from this data. Since this is not sure about the location of the centroid, adjust the centroid location based on the current updated data. Then assign all the data to this new centroid. This process is repeated until no data is moving to another cluster anymore. Mathematically this loop can be proved convergent.

4.6 Conclusion

Here, in this chapter, ABC and K-Mean clustering algorithm are discussed in detail. ABC is one of the recently developed population based algorithms which has shown impressive performance over other Evolutionary Algorithms (EAs). ABC is a metaheuristic algorithm for numerical optimization inspired from intelligent foraging behavior of honey bees. ABC results presented by researchers are better than other optimization techniques like Ant Colony Optimization, Particle Swarm Optimization, Genetic Algorithm and Simulated Annealing. K-means is one of traditional unsupervised learning algorithms that are useful in solving clustering problems. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume K clusters) fixed apriori. The main idea is to define K centers, one for each cluster. These centers should be placed in a cunning way because of different location causes different result.

CHAPTER 5

IMPLEMENTATION

In this chapter, firstly, MATLAB software, developed for BTS location optimization problem, is presented. Secondly, implementation of algorithmic flow of ABC and K-mean clustering in matlab environment along with optimization toolbox, are discussed, in detail.

5.1 Introduction

BTS localization is a complex optimization problem. A few of the characteristics of BTS that considered during optimization are received power, path loss and attenuation. There are no simple formulas due to the complex relationships between these parameters. Experiments are conducted using MATLAB 2007a version. Required coverage area 100 X 100. Once the site coordinates are evolved, the next step is to calculate the path loss, received power and attenuation from particular BTS to a receiving bin (Mobile Station or subscriber). The received power, path loss and attenuation are main parameters of considerations during the process of optimization and results are then to be compared with traditional method of clustering i.e. K-mean clustering. The Simulation was carried out with the following parameters settings: Transmit power 500 mW, Frequency 850 MHz, BTS antenna height h_{BTS} is 20 m to 200 m and MS antenna height h_{MS} is 1m to 10 m. No. of required BTSs = 2 (represented by blue color) and No. of MSs = 25 (represented by red color). Calculated the Path loss, attenuation and received power using Hata's Equation Hata [1980]. Optimized BTS locations are represented by green color and MSs represented by red color. Maximum fitness, F, is achieved.

5.2 MATLAB Environment

A programming platform of MATLAB 2010b will be created and reviewed for developing ABC and K-Mean clustering algorithms for BTS localization problem. MATLAB is a high-level language and interactive environment that enables you to perform computationally intensive tasks faster than with traditional programming languages such as C, C++, and Fortran. We can use MATLAB in a wide range of applications, including signal and image processing, communications, control design, test and measurement, financial modeling and analysis, and computational biology. Add on toolboxes (collections of special-purpose MATLAB functions) extend the MATLAB environment to solve particular classes of problems in these application areas. MAT- LAB provides a number of features for documenting and sharing your work. You can integrate your MATLAB code with other languages and applications, and distribute your MATLAB algorithms and applications. With the MATLAB language, you can program and develop algorithms faster than with traditional languages because you do not need to perform low-level administrative tasks, such as declaring variables, specifying data types, and allocating memory. In many cases, MATLAB eliminates the need for for loops. As a result, one line of MATLAB code can often replace several lines of C or C++ code.

5.2.1 Major advantages using MATLAB

1. High-level language for technical computing
2. Development environment for managing code, files, and data
3. Interactive tools for iterative exploration, design, and problem solving
4. Mathematical functions for linear algebra, statistics, Fourier analysis, filtering, optimization, and numerical integration
5. 2-D and 3-D graphics functions for visualizing data
6. Tools for building custom graphical user interfaces

7. Functions for integrating MATLAB based algorithms with external applications and languages, such as C, C++, Fortran, Java, COM, and Microsoft Excel

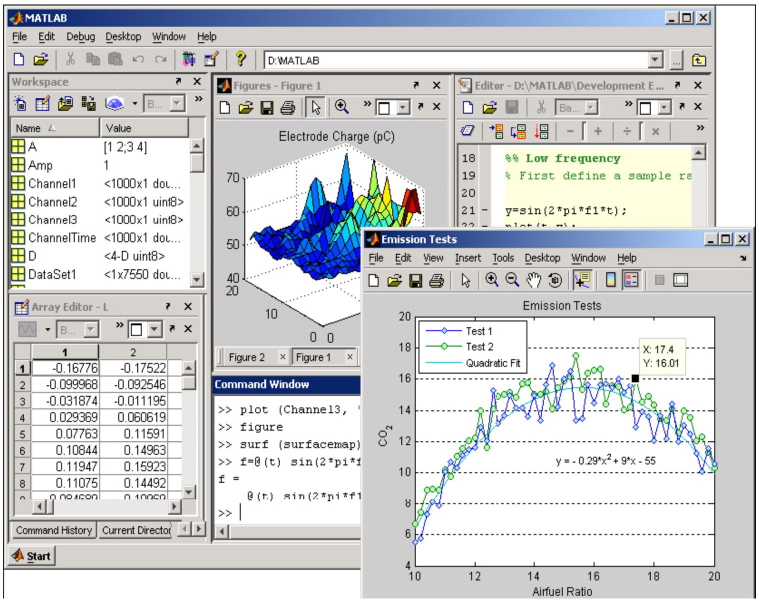

FIGURE 5.1: The MATLAB environment

5.2.2 Optimization Toolbox

BTS localization is done in two algorithm, first is K-mean clustering algorithm without any optimization technique and second is ABC algorithm that used to apply ABC technique for optimal locations of BTSs. Develop K-mean clustering and ABC algorithms using Optimization Toolbox.

Important features of optimization toolbox

1. Interactive tools for defining and solving optimization problems and monitoring solution progress.
2. Solvers for nonlinear and multiobjective optimization.
3. Solvers for nonlinear least squares, data fitting, and nonlinear equations.
4. Methods for solving quadratic and linear programming problems.
5. Methods for solving binary integer programming problems.
6. Parallel computing support in selected constrained nonlinear solvers.

5.3 ABC Algorithm

The ABC algorithm parameters are chosen to be: colony size (number of bees) as 100, number of employed bess/ food patches as half of the colony size, number of iterations as 50 number of runs as 100.

(b) No. of Food Source = No. of BTS.

(c) Required coverage area 100×100 sq. units.

(c) colony size = coverage area.

Algorithm 2 ABC Algorithmic Flow

1: Generate the initial solutions (positions of food sources) randomly and evaluate them.

2: For each solution x_i, determine a neighbor v_i using (1) and perform a greedy selection between x_i and v_i.

3: Calculate the probabilities for the solutions using (2).

4: Use the roulette wheel selection method to place the onlookers on the food sources and improve the corresponding solutions (as in step 2).

5: Determine the abandoned solution (if any) and replace it with a new randomly produced solution.

6: Record the best solution obtained till now.

7: Repeat steps 2 to 6 until MCN cycles are completed.

5.4 K-Means Clustering Algorithm

K-means is one of traditional unsupervised learning algorithms that are useful in solving clustering problems. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume K clusters) fixed apriori. The main idea is to define K centers, one for each cluster. These centers should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other [Likas et al., 2003]. The next step is to take each point belonging to a given data set and associate it to the nearest center. When no point is pending, the first step is completed and an early group age is done. At this point we need to

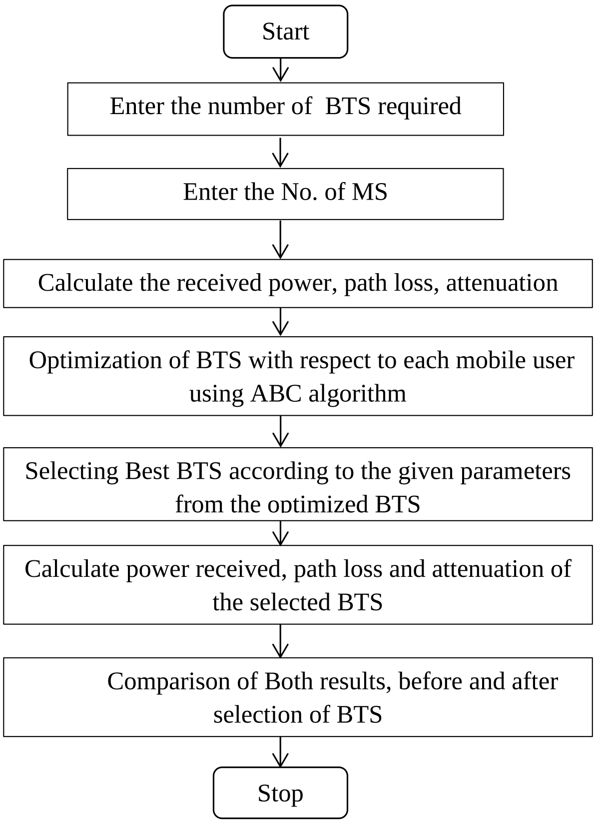

FIGURE 5.2: Flowchart for Selecting an Optimal Number of BTS Locations

re-calculate K new centroids as barycenter of the clusters resulting from the previous step. These K new centroids, a new binding has to be done between the same data set points and the nearest new center. A loop has been generated. As a result of this loop may notice that the K centers change their location step by step until no more changes are done or in other words centers do not move any more. Finally, this algorithm aims at minimizing an objective function know as squared error function given by (4.4)

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} (\|x_i - v_j\|)^2 \tag{5.1}$$

where $\|x_i - v_j\|$ is the Euclidean distance between x_i and v_j. $'c_i'$ is the number of data points in i^{th} cluster. $'c'$ is the number of cluster centers.

The basic step of K-means clustering is simple. In the beginning, number of cluster K are determined and assume the centroid or center of these clusters. Take any random objects as the initial centroids or the first K objects can also serve as the initial centroids. If the number of data is less than the number of cluster then assign each data as the centroid of the cluster. Each centroid will have a cluster number. If the number of data is bigger than the number of cluster, for each data, calculate the distance to all centroid and get the minimum distance. This data is said belong to the cluster that has minimum distance from this data. Since this is not sure about the location of the centroid, adjust the centroid location based on the current updated data. Then assign all the data to this new centroid. This process is repeated until no data is moving to another cluster anymore. Mathematically this loop can be proved convergent.

5.5 Fitness Algorithm

In the algorithm, one half of the population consists of employed bees and the other half consists of onlooker bees. The number of food sources equals the number of employed bees. During each cycle, the employed bees try to improve their food sources. Each onlooker bee then chooses a food source based on the nectar amount available at that food source. An employed bee whose food source is exhausted becomes a scout bee. The scout bee then searches for a new food source [Narasimhan, 2009].

The position of a food source represents a solution for an optimization problem. The nectar amount of the food source is the fitness of the solution. Each solution is represented using a D-dimensional vector. Here, D is the number of optimization parameters. Initially, SN solutions are generated randomly, where SN equals the number of employed bees. Let MCN be the maximum number of cycles that the algorithm would run. During each cycle, the employed and onlooker bees improve the solutions through a neighborhood search. A new solution v_i in the neighborhood of an existing solution x_i is produced as follows:

$$v_{ij} = x_{ij} + \Phi_{ij}(x_{ij} - x_{kj}) \tag{5.2}$$

where k=1, 2, ..., SN and Φ is a random number between [-1, 1] and j=1, 2,..., D. k and j are chosen randomly. A greedy selection is then performed between x_i and v_i.

The onlooker bees are placed on food sources using the roulette wheel selection method [**?**]. An onlooker bee thus chooses a food source at position x_i with a probability p_i calculated as follows:

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{5.3}$$

Here, fit_i is calculated using the following equation:

$$fit_i = \begin{cases} \frac{1}{1+fi} & \text{if } fi \leq 0 \\ 1 + abs(fi) & \text{if } fi \geq 0 \end{cases} \tag{5.4}$$

where f_i is the fitness value of the solution.

A solution representing a food source is abandoned by an employed bee if it cannot be improved for a predetermined number of trials given by the parameter limit. The employed bee then becomes a scout bee and randomly produces a new solution replacing the existing solution. The value of limit is generally chosen as SNxD.

5.6 Conclusion

In this chapter, implementation of ABC algorithms are discussed. Simulation results to analyze the performance of ABC and K-mean clustering are represented in next chapter for the application of optimizing BTS localization for maximization of fitness function.

CHAPTER 6

SIMULATION RESULTS

As already discussed, localization of BTS is not a easy task due to large number of geometrical parameters. MATLAB programming platform is used for coding of ABC and K-Mean clustering algorithms to optimized the BTS location. This chapter presents average of 100 runs to conclude, finally, the comparative performance of stochastic ABC and K-Mean clustering algorithms.

6.1 Introduction

ABC is one of the recently developed population based algorithms which has shown impressive performance over other Evolutionary Algorithms (EAs). ABC is a metaheuristic algorithm for numerical optimization inspired from intelligent foraging behavior of honey bees and is investigated, in this thesis work, to localize Base Transceiver Stations (BTSs) so as to cover maximum number of subscribers. ABC results presented in this work are better than K-Means Clustering Algorithm.

6.2 Simulation Platform

The MATLAB programming platform is used for coding of ABC and K-Means Clustering algorithms to optimized the BTSs locations.

In this chapter, performance of ABC and K-Means Clustering algorithm to maximize the fitness function.

6.3 Simulation Results

The evolutionary simulation results for performance comparison are presented, one by one as follows:

6.3.1 BTS localization Using K-Means Clustering Algorithm

K-means is one of traditional unsupervised learning algorithms that are useful in solving clustering problems. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume K clusters) fixed apriori. The main idea is to define K centers, one for each cluster. These centers should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other [Likas et al., 2003]. The next step is to take each point belonging to a given data set and associate it to the nearest center. When no point is pending, the first step is completed and an early group age is done. At this point we need to re-calculate K new centroids as barycenter of the clusters resulting from the previous step. These K new centroids, a new binding has to be done between the same data set points and the nearest new center. A loop has been generated. As a result of this loop may notice that the K centers change their location step by step until no more changes are done or in other words centers do not move any more. Finally, this algorithm aims at minimizing an objective function know as squared error function given by (6.1)

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} (\|x_i - v_j\|)^2 \tag{6.1}$$

where $\|x_i - v_j\|$ is the Euclidean distance between x_i and v_j. $'c_i'$ is the number of data points in i^{th} cluster. $'c'$ is the number of cluster centers [?].

The K-Mean clustering algorithm parameters are chosen to be: Number of clusters (K clusters), No. of centers (K centers, one for each cluster).

(a) No. of centers = No. of BTS.

(b) Required coverage area 100×100.

Experiments are conducted using MATLAB 2007a version. Required coverage area 100 X 100. Once the site coordinates are evolved, the next step is to calculate the path loss, received power and attenuation from particular BTS to a receiving bin (Mobile Station or subscriber). The received power, path loss and attenuation are main parameters of considerations during the process of optimization using traditional method of clustering i.e. K-mean clustering. The Simulation was carried out with the following parameters settings: Transmit power 500 mW, Frequency 850 MHz, BTS antenna height h_{BTS} is 20 m to 200 m and MS antenna height h_{MS} is 1m to 10 m. No. of required BTSs = 2 (represented by blue color) and No. of MSs = 25 (represented by red color) shown in fig. 1. Calculated the Path loss, attenuation and received power using Hata's Equation Hata [1980]. Optimized BTS locations are represented by green color and MSs represented by red color shown in fig. 2 using K-Mean clustering.

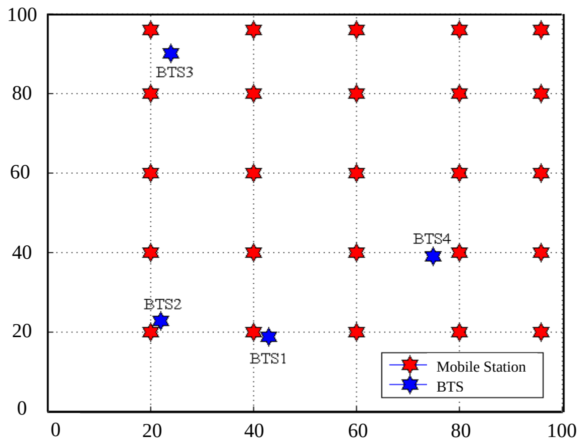

FIGURE 6.1: Random Mobile Station and BTS Locations

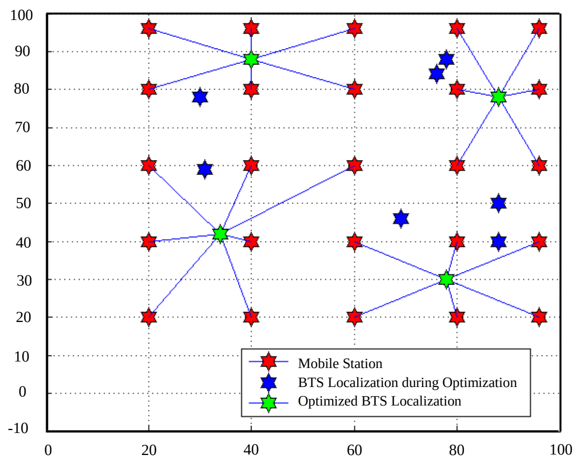

FIGURE 6.2: Optimized BTS Locations using K-Mean Clustering

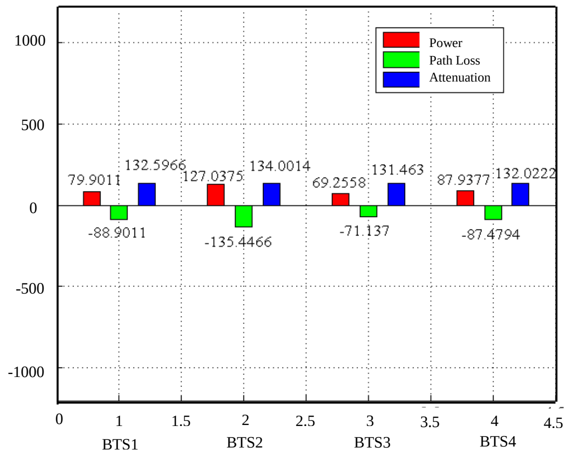

FIGURE 6.3: Power, Path- Loss and Attenuation using K-Mean Clustering

6.3.1.1 BTS localization Using ABC algorithm

The main objective of the present work is to optimally locate of BTSs, so that minimum number of BTS can be installed to cover larger number of subscribers at lesser infrastructural cost. The problem of optimization of BTS locations can thus be stated as: Given an area to cover on with potential subscriber density distribution, identify the optimal cell geometry and locations of BTSs. Our problem is to optimize BTS locations with respect to each MS using ABC algorithm. Artificial Bee Colony (ABC) algorithm is a metaheuristic search algorithm and is investigated, in this work, to localize BTSs so as to cover maximum number of subscribers. The results are then compared with K-Mean clustering method. The received power, path loss and attenuation are main parameters of considerations during the process of optimization. According to the given parameters best BTSs are selected from the optimized BTS locations.

The ABC algorithm parameters are chosen to be: colony size (number of bees) as 100, number of employed bess/ food patches as half of the colony size, number of iterations as 50 number of runs as 100.

(a) No. of Food Source = No. of BTS.

(b) Required coverage area 100×100 sq. units.

The fitness of a solution is decided on the basis of three main parameters: (a) Power received, P_r, (b) Path loss, L_p, and (c) Attenuation, A, using (6.2), (6.3) and (6.4)

$$P_r = 10\log_{10}(P_t) - abs(L_p) \tag{6.2}$$

$$L_p = 66.55 + (26.16)\log_{10} f - 13.82\log_{10} h_{BTS} - 3.2\log_{10} 11.75 h_{MS}$$
$$+44.9 - 6.55\log_{10} h_{BTS}\log_{10} d \quad (6.3)$$

$$A = 42.6 + 20\log_{10} f + 26\log_{10} d \quad (6.4)$$

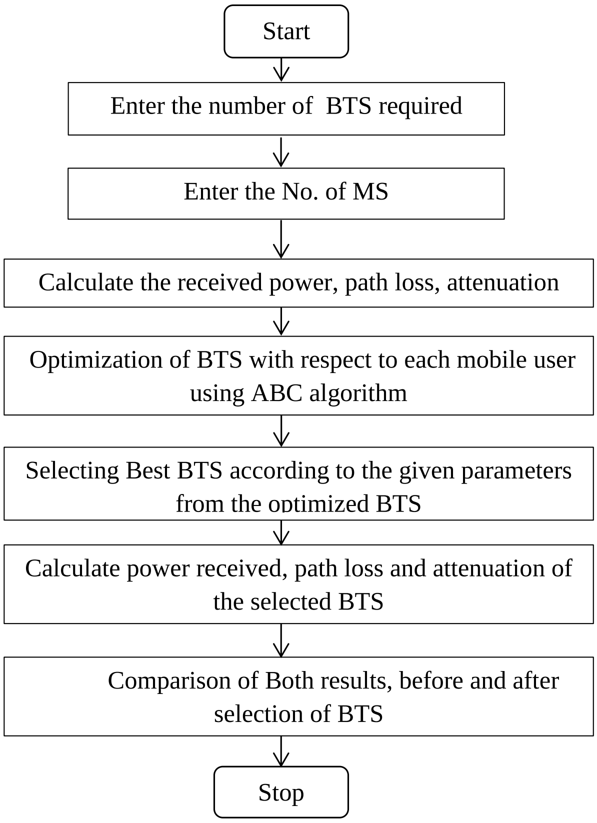

FIGURE 6.4: Flowchart for Selecting an Optimal Number of BTS Locations

Path loss is determined based on three parameters. viz. (1) Transmit power P_t=500 mW (2) Frequency f=850 MHz and (3) BTS antenna height h_{BTS} = 20m to 200 m and (4) Mobile station antenna height h_{MS} = 1m to 10 m and d is distance between MS and BTS Hata [1980].

No. of required BTSs = 3 (represented by blue color) and No. of MSs = 25 (represented by red color) are shown in fig. 1. Calculated the Path loss, attenuation and received power using Hata's Equation Hata [1980]. Optimized BTS locations are represented by green color

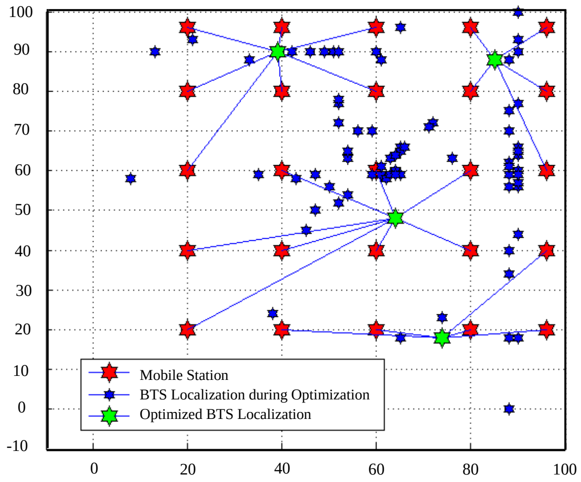

FIGURE 6.5: Optimized BTS Locations using ABC Algorithm

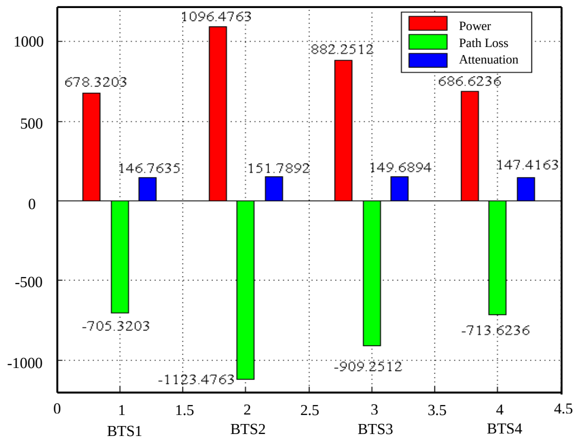

FIGURE 6.6: Power, Path- Loss and Attenuation using ABC

and MSs represented by red color are shown in fig. 6.2. Maximum fitness, F, is achieved given by equation (6.5).

$$F = \frac{1}{L_p A} abs(P_r) \tag{6.5}$$

The ABC algorithm requires a number of parameters to be initialized, namely: number of bees, number of food patches selected for neighborhood searching, number of employed bees (same as food sources), number of onlooker bees, limit for an employed bee to become scout, and the stopping criterion.

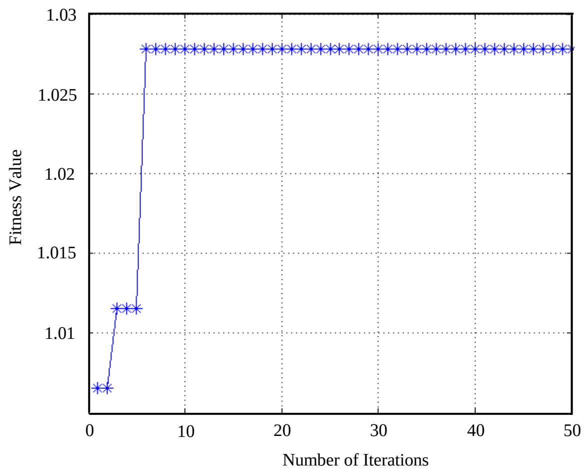

FIGURE 6.7: Fitness Versus number of Iterations using ABC algorithm

6.3.2 The Best Performance Comparison

The received power, path loss and attenuation are main parameters of considerations during the process of optimization using ABC algorithm and results are then to be compared with traditional method of K-mean clustering and shown better in following figures. The Simulation was carried out with the following parameters settings: Transmit power 500 mW, Frequency 850 MHz, BTS antenna height h_{BTS} is 20 m to 200 m and MS antenna height h_{MS} is 1m to 10 m. No. of required BTSs = 2 (represented by blue color) and No. of MSs = 25 (represented by red color) shown in fig. 1.

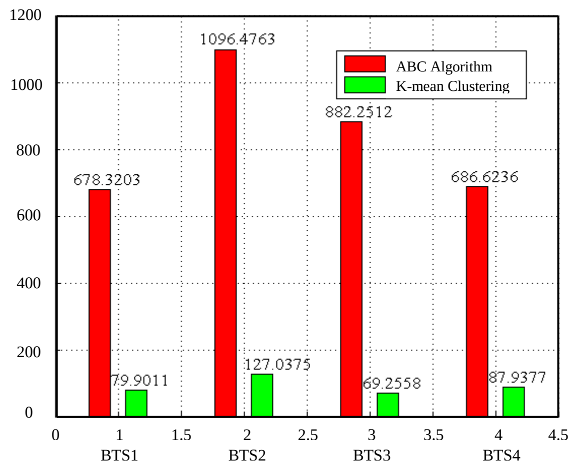

FIGURE 6.8: Power Comparison graph for ABC and K-Mean Clustering Algorithms

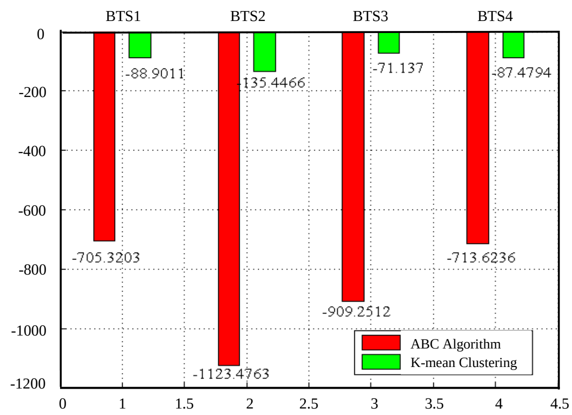

FIGURE 6.9: Path Loss Comparison graph for ABC and K-Mean Clustering Algorithms

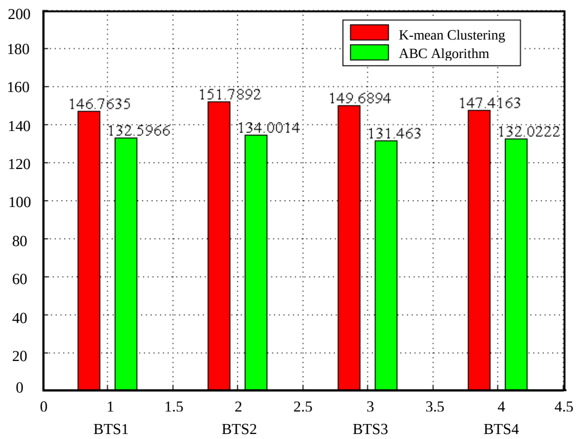

FIGURE 6.10: Attenuation Comparison graph for ABC and K-Mean Clustering Algorithms

6.4 Overall Result Analysis

The received power, path loss and attenuation are main parameters of considerations during the process of optimization using ABC algorithm and results are then to be compared with traditional method of K-mean clustering and shown better in comparison table. Average obtained during simulations are tabulated in Table 6.1. Following observation can be drawn, finally,

6.5 Conclusion

In this chapter, all the results obtained from ABC and K-mean clustering are compared. The received power, path loss and attenuation are main parameters of considerations during the process of optimization using ABC algorithm and results are then to be compared with traditional method of K-mean clustering and shown better in comparison table and figures.

Table 6.1: Comparison of result parameters between ABC and K-Mean clustering algorithm

PARAMETERS	BTS	USING ABC ALGORITHM	USING K-MEAN CLUSTERING
POWER	BTS1	678.3203	79.9011
	BTS2	1096.4763	127.0375
	BTS3	882.2512	69.2558
	BTS4	686.6236	87.9377
PATH-LOSS	BTS1	-705.3203	-88.9011
	BTS2	-1123.4763	-135.4466
	BTS3	-909.2512	-71.137
	BTS4	-713.6236	-87.4794
ATTENUATION	BTS1	132.5966	146.7635
	BTS2	134.0014	151.7892
	BTS3	131.463	149.6894
	BTS4	132.0222	147.4163

CHAPTER 7

CONCLUSION AND FUTURE SCOPE

Research is an iterative process very similar to ABC where researchers keep on proposing and implementing new ideas based on their previous successes and the successes observed by other researchers in the area. Various research observations are presented at the end of previous chapter as conclusions but limited to scope of this thesis only. This chapter aims to conclude the thesis as a whole, and to aggregate all the offshoots found throughout the work.

7.1 Introduction

Karaboga developed a new optimization algorithm called the Artificial Bee Colony (ABC) algorithm (Karboga, 2005). The ABC algorithm was firstly introduced for numerical optimization problems based on the foraging behavior of a honey bee swarm. Further improvements of the ABC algorithm have been carried out by Karaboga and Basturk (2007). In this model, the foraging bees are classified into three different types: employed bees, onlookers and scouts. A bee which has found a food source to exploit is called an employed bee. Onlookers are those waiting in the hive to receive the information about the food sources from the employed bees and Scouts are the bees which are randomly searching for new food sources around the hive. A number of researches studied and applied the Artificial Bee

Colony on several study cases ranging from normal equations to structural design problems. Karaboga and Basturk presented the main outlines of the ABC algorithm (Karaboga & Basturk, 2008). Later on, Akay and Karaboga (2009) applied the ABC algorithm on numerical test functions and compared the results with well-known algorithms such as the GA, Particle Swarm Optimization (PSO) and HS.

7.2 Conclusion

In this work a relatively new member of swarm intelligence family that is named as "artificial bee colony" is explained in detail. Actually, different names were used in the literature for the algorithms inspired from natural honey bees. Here we prefer to use the name "artificial bee colony" to reflect population characteristic of the algorithm. A very detailed literature review along with a categorization is presented in this study. All accessible previous work on bee based optimization algorithms is tried to be reviewed. Most of the work in the literature is carried out in last two years and researchers mainly concentrated on continuous optimization and TSP problems. Previous work has presented that bee inspired algorithms have a very promising potential for modelling and solving complex optimization problems.

In this thesis work ABC algorithm is applied to determine the optimal location of BTS, avoiding the greedy exhaustive search. The proposed work has ability to achieve optimal solution of coverage problem with minimum number of BTS in cellular networks. This approach cultivates an innovative idea employing the ABC algorithm with enhanced fidelity. The results show that the ABC approach is effective and robust for efficient coverage problem of BTS location and is considered to give almost the optimal solution in wireless communication network.

7.3 Future Scope

In future, focus can be given to achieve 100% coverage with minimum number of BTS. The study of the 100% coverage using various optimal search techniques also presents several interesting challenges. Our research is still under progress and we are hoping to find effective solutions for large coverage area and with some other no. of parameters to localize the BTS. These problems are over complex, therefore their solution can be considered as a very good indicator for the potential of the nature inspired algorithms including "artificial bee colony".

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INDEX