CHAPTER 5

ABC BASED MPSS

5.1 SWARM INTELLIGENCE - AN OVERVIEW

Since ever, many natural systems of the most creatures in the world are very rich topics for the scientific researchers. However, a simple individual behavior can cooperate to create a system able to solve a real complex problem and perform very sophisticated tasks. In reality there are many patterns of such systems like ant colonies, bird flocking, fish shoaling, animal herding, bacterial growth, bee colonies and human neuron system as per Saif Mahmood Saab et al (2010).

Artificial Intelligence (AI) is a concept of study and research for finding relationships between cognitive and computation theories. Owaied and Abu-Arr’a (2007) represented the relationship as data structures, search techniques, problem solving methods, or representation forms for knowledge. These systems are working either under supervision or without supervision. Most of social insects work without supervision. Eric Bonabeau and Christopher Meyer (2001) suggest that their teamwork is largely self-organized, and coordination arises from the different interactions among individuals in the system. These interactions might be primitive, like ants follow odor trails, or more complex, like a honey bee dancing. The collective behavior that emerges from a group of social insects has been artificially represented as a technique known as Swarm Intelligence (SI). However, SI is a type of AI where the term swarm is used in a general manner to refer to any
restrained collection of interacting agents or individuals. SI systems are typically made up of a population of self-organized individuals interacting locally with one another and with their environment. Although there is normally no centralized control structure dictating how each individual should behave, local interactions between all individuals often lead to the emergence of global behavior.

Yan-fei Zhu and Xiong-min Tang (2010) has research that swarm intelligence as an active research area by a number of research scientists in various domains which simulates the intelligence in swarms of insects or animals. A number of techniques have been presented to formulate the intelligent nature of honey bee swarms. Real-world problems generally have several design parameters that should be regarded in the design process. Algorithms that are not hearty to large-scale issues cannot protect their efficiency against high dimensionality.

There is only one employed bee for every food source. The scouts in every bee colony act as the explorers of the colony. The scouts are featured by low search costs and a low average in food source quality. Rarely, the scouts can by chance identify rich, completely unknown food sources. In ABC algorithm, the location of a food source denotes a probable solution to the optimization problem and the nectar amount of a food source match up to the quality (fitness) of the associated solution. A number of algorithms have been presented in order to deal with a number of issues. It is known for their capability to construct low cost, fast and practically accurate solutions for the numerical optimization.

5.1.1 Fundamentals of Swarm Intelligence

Two fundamental concepts, self-organization and division of labor, are necessary and sufficient properties to obtain swarm intelligent behavior
such as distributed problem solving systems that self-organize and adapt to the given environment (Dervis Karaboga 2005).

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 (1999) have characterized three basic property on which self-organization relies: Positive feedback, negative feedback and fluctuations:

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

- 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.

- 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.
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 activities of others.

Inside a swarm, there are different tasks, which are performed simultaneously by specialized individuals. This kind of phenomenon is called division of labor. Simultaneous task performance by cooperating specialized individuals is believed to be more efficient than the sequential task performance by unspecialized individuals. Division of labor also enables the swarm to respond to changed conditions in the search space.

5.1.2 Relation between ABC algorithm and Swarm Intelligence

The ABC algorithm is a metaheuristic algorithm that relies on swarm intelligence rather than evolutionary procedures. Swarm intelligence has become a research interest to many scientists of related fields in recent years. It has defined the swarm intelligence as “any attempt to design algorithms or distributed problem-solving devices inspired by the collective behavior of social insect colonies and other animal societies”. Bonabeau et al (1999) 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.
5.2 NATURE INSPIRED OPTIMIZATION ALGORITHMS

The outlook of modern scientific society has been focused to model and handle composite optimization issues by means of natural metaphors. This is primarily due to ineffectiveness of traditional optimization algorithms in handling superior scale combinatorial and highly non-linear issues. The condition is not much different if integer or discrete decision variables are needed in most of the linear optimization models as well. One of the main characteristic features of the traditional optimization algorithms is their rigidity to adapt the solution algorithm to a given problem. Usually, a given problem is modeled in such a way that a traditional algorithm like simplex algorithm can deal with it. This usually needs making numerous assumptions which might not be easy to authenticate in a variety of scenarios.

In order to overcome these drawbacks, more flexible and adaptable general purpose techniques are required. It should be effortless to adapt these algorithms to model a given issue as close as possible to reality. Based on this inspiration, several naturally inspired approaches such as genetic algorithms, simulated annealing and tabu search were developed in the literature. It has also been indicated that these algorithms can offer far better solutions compared to traditional algorithms. A group of naturally inspired approaches which are called as swarm intelligence is mainly focused on insect behavior to develop certain meta-heuristics which can imitate problem solving abilities of the insects.

Ant Colony Optimization, Particle Swarm Optimization, WASP (Insect) NETs etc., are a few of the well known algorithms that imitate behavior of the insects in problem modeling and solution. Artificial Bee Colony is a relatively new member of swarm intelligence. ABC models the natural behavior of real honey bees in food foraging. Honey bees make use of various approaches like waggle dance to optimally determine food sources
and to search for new ones. This makes ABC an efficient technique for developing novel intelligent search approaches. Figure 5.1 illustrates the performance comparison of the traditional optimization techniques and the modern heuristic optimization techniques.

5.2.1 Classical Optimization Techniques

The block for Classical Optimization Techniques depicts that these algorithms are problem dependent and does not provide accurate results for more complex problems. The block also illustrates that modification to the classical optimization technique is not easy.

*Figure 5.1 A Pictorial Comparison of Classical and Modern Heuristic Optimization Strategies*
Problem Dependent: It is a well known fact that traditional optimization approaches impose a number of drawbacks on solving mathematical programming and operational research models. This is primarily due to intrinsic solution methods of these techniques.

Solution Techniques: Solution approaches of traditional optimization algorithms are usually based on the type of objective and constraint functions (linear, non-linear, etc.) and the type of variables used in the problem modeling (integer, real, etc.). Their competence is based on the size of the solution space, number of variables and constraints used in the problem modeling, and the structure of the solution space (convex, non-convex, etc.). Moreover, the algorithms also do not provide common solution approaches that can be employed to problems in which different type of variables, objective and constraint functions are used.

Drawbacks: Simplex algorithm can be employed to handle models with linear objective and constraint functions; whereas geometric programming can be employed to solve non-linear models with a polynomial or sigmoid objective function, etc. (Baykasoulu 2001). But, a majority of the optimization issues need different types of variables, objective and constraint functions at the same time in their formulation. Therefore, traditional optimization techniques are usually inappropriate for many critical problems.

5.2.2 Nature Inspired Heuristics Algorithms

Problem Independent: Various researchers have made efforts in order to adapt many optimization problems to the traditional optimization procedures. It is usually very tough to formulate a real life problem that adapts a particular solution process. To attain this result, it is essential to make certain modifications on the original problem parameters (rounding variables, softening constraints, etc.). This surely has an influence on the
solution quality. A new group of problems and model independent nature inspired heuristic optimization techniques were developed by researchers to overcome limitations of the traditional optimization procedures. The Nature Inspired Heuristics block illustrates that the modifications can be easily applied to the modern heuristic approaches to solve complex and critical issues. These optimization approaches are efficient and flexible.

5.3 MODERN HEURISTICS APPROACHES

Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) are the most widely used efficient nature inspired modern heuristic optimization algorithms. This section discusses about the most recent optimization techniques namely ACO and ABC.

5.3.1 Basic Ant Colony Optimization

Marco Dorigo and Thomas Stützle (2004) investigated that ACO is a novel natural computation algorithm inspired from the natural behaviors of ant colony. The parameters of ACO algorithms are chosen by means of a logical process such as a genetic algorithm in order to attain significant performance. The conventional ACO is a good combination optimization technique. ACO is originally developed to solve the complicated combination optimization issues such as Travelling Salesman Problem (TSP). It looks for optimal solution by taking in to account both local heuristics and prior knowledge (Ahmed 2005). ACO is a metaheuristic to handle combinational optimization issues through principles of communication about the paths to locate food sources by marking these paths with pheromone.

The pheromone trails can guide other ants to the food sources. It was observed that real ants were capable to choose the shortest path between
their nest and food resources, in the presence of alternate paths between the
two. Ants deposit a chemical substance called pheromone on their way. When
the ants reach at a decision point, they make a probabilistic choice influenced
by the intensity of pheromone substance. When the ants return back, the
probability of selecting the same path is higher, because of the increase of
pheromone.

The new pheromone will be released on the selected path. Marco
Dorigo and Gianni Di Caro (1999) has described that this behavior has an
autocatalytic effect as the very fact of selecting a path will increase the
amount of pheromone on the equivalent path which in turn will make it more
attractive for future ants to follow. Shortly all ants will chose the shortest
path.

5.3.2 Problems Identified in ACO

Since, the tracking is based on the pheromone values at each node,
the values of them must be updated frequently to keep its current level due to
its evaporation. This updating process presents substantial overhead in the
optimization process. The final optimal solution can be obtained by
examining all of the solution candidates created by ant exploration. Since, the
process is a sequential one in which the solution selection is done only at the
end, leads to computational overhead and memory limit problems. Suppose a
group of ten ants have been deployed for the optimal solution generation, and
if this group of ants fails, then a new group of ten other ants have to be
deployed. The time spent for the initial process will be a mere waste and leads
to substantial time overhead.
5.3.3 Solutions Provided by ABC

Since, ABC is a Non-Pheromone based technique; there is no need for the updating of pheromone values. The communication between the bees is by means of waggle dance; that is done by setting a status flag for each bee. Parallel behavior of group of bees (multi-threading) makes the algorithm faster in reaching near global optimal solution. The final optimal solution is the improvement done during each iteration of the bees' exploration process. There is no need to examine all the solution candidates generated from the beginning to the end at the final step. Hence, computational overhead and memory limit problems are balanced. If there is no improvement in the current solution, then the scout will start a new search and a new set of test cases are generated. There is no need to deploy more bees for this case. Hence, time overhead is reduced.

This approach uses the ABC for the stabilization of power systems. The main advantages of using ABC are less computational overhead and reduced memory limit problems.

5.4 A NATURAL FORGING BEHAVIOR OF BEES

A branch of nature inspired algorithms which are called as swarm intelligence is focused on insect behavior in order to develop some meta-heuristics which can mimic insects’ problem solution abilities. A bee colony can be thought of as a swarm whose individual agents are bees. Each bee at the low-level component works through a swarm at the global level of component to form a system. Thus, the system global behavior is determined from it is individual's local behavior where the different interactions and coordination among individuals lead to an organized teamwork system. Nebojsa Bacanin et al (2011) characterize the system by interacting collective
behavior through labor division, distributed simultaneous task performance, specialized individuals, and self organization.

The exchange of information among bees leads to the formation of a tuned collective knowledge. A colony of honey bees consists of a queen, many drones (males) and thousands of workers (non-reproductive females). The queen's job is to lay eggs and to start new colonies. The sole function of the drones is to mate with the queen and during the fall they are ejected from the colony. The worker bees build honeycomb, and the young, clean the colony, feed the queen and drones, guard the colony, and collect food. As nectar is the bees energy source, two kinds of worker bees are responsible for food. These are scout bees and forager bees. A bee does many things in its life history, and does not become a scout/work bee until late in its life.

While scout bees carry out the exploration process of the search space, forager bees control the exploitation process. However, exploration and exploitation processes must be carried out together by the colony’s explorers and colony’s exploiters. As the increase in the number of scouts encourages the exploration process, the increase of foragers encourages the exploitation process.

Studying the foraging behavior leads to optimal foraging theory that directs activities towards achieving goals. In other words, the swarm of bees behaves in such a way as to find and capture the food that containing the most energy while expending the least possible amount of time in real variables. There are two forms of scenarios for any bee in forging process which are either scout or forager. The following subsections present these two scenarios:
5.4.1 An Overview of Bee Colony Optimization

Within the Bee Colony Optimization Metaheuristic (BCO), agents that we call artificial bees collaborate in order to solve difficult combinatorial optimization problem. All artificial bees are located in the hive at the beginning of the search process. During the search process, artificial bees communicate directly. Each artificial bee makes a series of local moves, and in this way incrementally constructs a solution of the problem. Bees are adding solution components to the current partial solution until they create one or more feasible solutions. The search process is composed of iterations. The first iteration is finished when bees create for the first time one or more feasible solutions. The best discovered solution during the first iteration is saved, and then the second iteration begins. Within the second iteration, bees again incrementally construct solutions of the problem, etc. There are one or more partial solutions at the end of each iteration. Dusan and Mauro (2008) tell that the analyst-decision maker prescribes the total number of iterations.

When flying through the space our artificial bees perform forward pass or backward pass. During forward pass, bees create various partial solutions. They do this via a combination of individual exploration and collective experience from the past.

After that, they perform backward pass, i.e. they return to the hive. In the hive, all bees participate in a decision-making process. We assume that every bee can obtain the information about solutions’ quality generated by all other bees. In this way, bees exchange information about quality of the partial solutions created. Bees compare all generated partial solutions. Based on the quality of the partial solutions generated, every bee decides whether to abandon the created partial solution and become again uncommitted follower, continue to expand the same partial solution without recruiting the nestmates,
or dance and thus recruit the nestmates before returning to the created partial solution.

Depending on the quality of the partial solutions generated, every bee possesses certain level of loyalty to the path leading to the previously discovered partial solution. During the second forward pass, bees expand previously created partial solutions, and after that perform again the backward pass and return to the hive. In the hive bees again participate in a decision-making process, perform third forward pass, etc. The iteration ends when one or more feasible solutions are created Goran et al (2007).

Alternatively, Leonardo Caggiani et al (2012) suggest that the forward and backward passes could be performed until some other stopping condition is satisfied. The possible stopping conditions could be, for example, the maximum total number of forward/backward passes, or the maximum total number of forward/backward passes between two objective function value improvements.

Within the BCO Metaheuristic, various sub-models describing bees’ behavior and/or “reasoning” could be developed and tested. In other words, various BCO algorithms could be developed. These models should describe the ways in which bees decide to abandon the created partial solution, to continue to expand the same partial solution without recruiting the nestmates, or to dance and thus recruit the nestmates before returning to the created partial solution.

5.4.2 Interactive Behavior of Bees

Interaction between insects contributes to the collective intelligence of the social insect colonies. These communication systems between insects have been adapted to scientific problems for optimization.
One of the examples of such interactive behavior is the waggle dance of bees during the food procuring. By performing this dance, successful foragers share the information about the direction and distance to patches of flower and the amount of nectar within this flower with their hive mates. So this is a successful mechanism which foragers can recruit other bees in their colony to productive locations to collect various resources. Bee colony can quickly and precisely adjust its searching pattern in time and space according to changing nectar sources as set by Adil Baykasoulu et al (2007).

The information exchange among individual insects is the most important part of the collective knowledge. Communication among bees about the quality of food sources is being achieved in the dancing area by performing waggle dance. The previous studies on dancing behavior of bees show that while performing the waggle dance, the direction of bees indicates the direction of the food source in relation to the Sun, the intensity of the waggles indicates how far away it is and the duration of the dance indicates the amount of nectar on related food source.

![Figure 5.2 Waggle Dance of Honey Bees](image)

Waggle dancing bees that have been in the hive for an extended time adjusts the angles of their dances to accommodate the changing direction
of the sun. Therefore bees that follow the waggle run of the dance are still correctly led to the food source even though its angle relative to the sun has changed. So collective intelligence of bees based on the synergistic information exchange during waggle dance.

Observations and studies on honey bee behaviors resulted in a new generation of optimization algorithms. In this chapter a detailed review of bee colony based algorithms is given.

5.4.3 Description of Behavior of Bees in Nature

Social insect colonies can be considered as dynamical system gathering information from environment and adjusting its behavior in accordance to it, while gathering information,

**Food Sources:** The value of a food source depends on different parameters such as its proximity to the nest, richness of energy and ease of extracting this energy.

(a) **Unemployed Foragers**

If it is assumed that a bee has no knowledge about the food sources in the search field, bee initializes its search as an unemployed forager. There are two possibilities for an unemployed forager as

**Scout Bee (S):** If the bee starts searching spontaneously without any knowledge, it will be a scout bee. The percentage of scout bees varies from 5% to 30% according to the information into the nest. The mean number of scouts averaged over conditions is about 10% (Seeley 1995).

**Recruit Bee (R):** If the unemployed forager attends to a waggle dance done by some other bee, the bee will start searching by using the knowledge from waggle dance.
In the Figure 5.3, Scout Bee represented by ‘S’ begins the foraging process. Recruit Bee represented by ‘R’, starts the searching process based on the knowledge of the waggle dance in area A and B.

(b) Employed Foragers (EF)

When the recruit bee finds and exploits the food source, it will raise to be an employed forager who memorizes the location of the food source. After the employed foraging bee loads a portion of nectar from the food source, it returns to the hive and unloads the nectar to the food area in the hive. There are three possible options related to residual amount of nectar for the foraging bee.

- If the nectar amount decreased to a low level or exhausted, foraging bee abandons the food source and become an unemployed bee.

- If there are still sufficient amount of nectar in the food source, it can continue to forage without sharing the food source information with the nest mates

- Or it can go to the dance area to perform waggle dance for informing the nest mates about the same food source. The probability values for these options highly related to the quality of the food source.

In the Figure 5.3, it is depicted that EF finds the food source based on the waggle dance of R and unloads the nectar from A and B.
Figure 5.3 Typical Behavior of Honey Bee Foraging

(c) Experienced Foragers

These types of foragers use their historical memories for the location and quality of food sources. It can be an inspector which controls the recent status of food source already discovered.

**Reactivated Forager (RF):** It can be a reactivated forager by using the information from waggle dance. It tries to explore the same food source
discovered by itself if there are some other bees confirm the quality of same food source.

**Experienced Scout Bee (ES):** It can be scout bee to search new patches if the whole food source is exhausted.

**Experienced Recruit Bee (ER):** It can be a recruit bee which is searching a new food source declared in dancing area by another employed bee.

In the Figure 5.3, RF explores the quality of the food source discovered by verifying whether other bees confirm the quality of the same food. Experienced Scout (ES) bee searches for new food source from the random point in search field. In the same way, Experienced Recruit (ER) bee searches for the new food source in the dancing area based on the waggle dance of employed bees (EF).

### 5.5 PROPOSED ABC TECHNIQUE FOR OPTIMIZATION OF MPSS

The model of multi-machine power system considered for this proposed approach is the same considered in the previous chapter which is shown in Figure 3.3. The multi-machine consists of 3-machine, 9-bus power system. $G_1$, $G_2$ and $G_3$ are the machines present in the multi-machine system taken into consideration. The proposed approach employs ABC algorithm to solve this optimization problem and search for optimal set of PSS parameters, \( \{K_i, T_{1i}, T_{3i}, i = 1, 2, \ldots, n_{PSS}\} \).

#### 5.5.1 Artificial Bee Colony Algorithm

This approach uses ABC algorithm for the stabilization of the power system. ABC algorithm is introduced by (Dervis Karaboga 2005).
ABC algorithm was formed by observing the activities and behavior of the real bees, while they were looking for the nectar resources and sharing the amount of the resources with the other bees.

Data flow creation around the beehive is a behavior of bees that involves the fundamentals of the swarm intelligence. There are three kinds of bees such as employed, onlooker and scouts. Each type of bees has a different role in the optimization process. Employed bees wait above the nectar source and keep the neighboring sources in memory. Onlooker bees get that data from employed bees and make a resource choice to collect the nectar. Also, the scouts are very much accountable for calculation. The algorithm comprises of three steps. In the first step, employed bees are sent to scamper for resources and the nectar amount is computed.

In the second step, onlooker bees make a resource choice appropriate to the data they took from identifying new nectar resources. Ultimately, in the third step, one of the employed bees is chosen at random as a scout bee and it is sent to the sources to identify new sources as developed by Arabia and Abdallah (2007). Half of the bees in the colony are chosen as employed and the rest half are chosen as onlooker bees in the algorithm. Therefore, the number of employed bees is equal to the number of nectar sources. The food sources in the approach refer to the probable solutions of the issue to be optimized. The nectar amount belonging to a source denotes the quality value which is said by that source as shown in Figure 5.4. The process of ABC algorithm is explained below:

A random population \((X_1, \ldots, X_S)\) is initialized. where, \(X_i = \{x_{i1}, x_{i2}, \ldots, x_{iD}\}\)

Each solution vector is generated using the following equation
\[ x_{ij} = x_{j\min} + (x_{j\max} - x_{j\min}) \text{rand}[0, 1] \]  
(5.1)

where, \( j = 1, 2, \ldots, D \)
\[ i = 1, 2, \ldots, w \]

\( x_{j\max} \) and \( x_{j\min} \) respectively represent the upper and lower bounds for the dimension \( j \).

Thus, in the first step of the ABC, random solutions are created in the particular range of the parameters \( x_i \) (\( i = 1, \ldots, w \)). where, \( w \) is the number of the food sources.

Secondly, each employed bee identifies new sources whose amounts are equal to half of the total sources. Equation 5.2 is used to find a new source \( v_{ij} \).

\[ v_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}) \]  
(5.2)

where, \( \varphi_{ij} \) denotes a uniformly distributed real random number within the range \([-1, 1]\)
\( k \) represents the index of the solution chosen randomly from the colony (\( k = \text{int}(\text{rand} * S) + 1 \))
\( j = 1 \ldots D \)

D denotes the dimension of the problem.

After generating the new food source, the nectar amount of it will be evaluated and a greedy selection will be performed. If the quality of the new food source is better than the current position, the employed bee leaves its position and moves to the new food source; in other words, if the fitness of the new food source is equal or better than that of \( X_i \), the new food source takes the place of \( X_i \) in the population and becomes a new member. Thus, after creating \( \overline{v_i} \), they compared \( \overline{x_i} \) solutions and the best one was used as the source.
Figure 5.4 Flowchart of ABC Algorithm

Initial food source position

Calculate the nectar amounts

Determine the new food position for the employed bees

Calculate nectar amounts

All onlookers distributed?

YES

Memorize the position of best food source

Find the abandoned food source

Produce new position for the exhausted food source

All onlookers distributed?

NO

Initial food source position

Determine the neighbor food source for the onlooker

Select a food source for the onlooker

NO
In the third step, onlooker bees select a food source with the probability given in Equation 5.3 produces a new source in selected food source site by equation (5.2). Once the new food source is generated, it will be evaluated and a greedy selection will be applied, same as the case of employed bees. As for employed bee, the better source is decided to be exploited.

\[ P_i = \frac{\text{fit}_i}{\sum_{j=1}^{S} \text{fit}_j} \]  \hspace{1cm} (5.3)

where, \( \text{fit}_i \) is the fitness of the solution \( x_i \).

Omkar and Senthilnath (2009) presented that scout bees are accountable for random researches in each colony. Scout bees do not use any pre knowledge and facts when they are looking for nectar sources, and as such, their research was randomly done completely. The scout bees are chosen among the employed bees with respect to the limit parameter. If a solution that denotes a source is not realized with in a particular number of trials, then this source is discarded. The bee of that source identifies new source as a scout bee. The number of incomings and outgoings to a source is obtained by the ‘limit’ parameter. Identifying a new source of a scout bee is given in Equation 5.4.

\[ x_{ij} = x_{j}^{\text{min}} + \left( x_{j}^{\text{max}} - x_{j}^{\text{min}} \right) \times \text{rand} \]  \hspace{1cm} (5.4)

Based on the above equation, each employed bee searches the neighborhood of its current food source to determine a new food source.

In ABC, the employed and the onlooker bees serve in the utilization process and the scouts serve in the process of exploration. Bees toil for the
maximization of the amount of the foods that are brought to the nest. The maximization of the objective function is $F(\theta_i)$. 

where, $\theta_i \in \mathbb{R}^p$ is done in the maximization problem

$\theta_i$ represent the position of the $i^{th}$ source

$F(\theta_i)$ denotes the nectar amount in this source

$P(c) = |\theta_i(c)|, i = 1,2,\ldots,S$ is the population of the sources including the positions of all the sources. Selecting a source of onlooker bees is based on the value of $F(\theta_i)$.

The more nectar amount of a source denotes more probability that the source would be selected. It means that, the probability of selecting a nectar source in the position is:

$$P_i = \frac{F(\theta_i)}{\sum_{k=1}^{S} F(\theta_k)} \quad (5.5)$$

$\theta_k(c)$, where $k$ is different from $i$, are randomly formed indices of a solution in the population.

After the onlooker bee observes the dance of the employed bees and selects the source with the equality (equation (5.6)), it identifies a neighboring source and takes its nectar. The position information of the chosen neighbor is computed by the following equation:

$$(c + 1) = \theta_i(c) \pm \phi(c) \quad (5.6)$$

where, $\phi(c)$ denotes evaluated by considering the difference of certain parts of $\theta_i(c)$ and $\theta_k(c)$. 

If the nectar amount of $\theta_{i}(c+1)$, $F(\theta_{i}(c+1))$, is greater than the nectar amount in the position $\theta_{i}(c)$, then the bee goes to its beehive and shares this data with the other bees and keeps $\theta_{i}(c+1)$ in the mind as a new position. Or else, it goes on keeping $\theta_{i}(c)$ in mind. If the nectar source of the position $\theta_{i}$ is not realized by the number of ‘limit’ parameter, then the source in the position $\theta_{i}$ is discarded and the bee of that source becomes scout bee. The scout bee creates random researches and identifies a new source and the newly found source is assigned to $\theta_{i}$. The algorithm iterates to the preferred cycle number, and the sources having the best nectar in mind denote the possible values of the variables. The obtained nectar amount denotes the solution of the object function.

Computational algorithms implementation steps are discussed below. These steps are simulated using MATLAB.

**Step 1: Initialization**

In the beginning, the ABC parameters have to be specified during initialization process. The main difficulty with the ABC program is that; an appropriate choice of ABC control parameters is necessary before applying the ABC program. The choice of parameters has been obtained by trial and error. In order to get better result in the development of the ABC program; the parameters must be selected carefully.

The proposed approach employs ABC algorithm to solve this optimization problem and search for optimal set of PSS parameters $\{K_i, T_{1i}, T_{3i}, i = 1, 2, \ldots, n\}$. where, $K_i$ is the stabilizer gain, $T_{1i}$ & $T_{3i}$ are the time constants and $n$ is the number of machines.
Step 2: Generate First Node

The first node will be selected by generating random populations of $K_i$, $T_{1i}$ and $T_{3i}$-based on the uniform distribution, ranging from 1 to n.

Step 3: State Transition Rule

At each construction step, bee (k) applies a state transition rule in order to decide which node to be visited next. The bee (k), which is currently positioned at current node (r) will move to the next node (s) by applying the state transition rule. By using this rule objective values $J$ for $K_i$, $T_{1i}$ and $T_{3i}$ are evaluated. Evaluation of the PSS parameters and modeling equations were discussed in chapter 3.

Step 4: Local Updating Rule

Local updating rule is a process used to change the amount of pheromone to the visited paths during the construction of solution. This local updating rule will shuffle the tours, so that the early nodes in one bee’s tour may be explored later in other bee’s tours. The amount of pheromone on visited paths will be reduced so that the visited paths become less desirable and therefore will be chosen with lower probability by the other bees in the remaining steps of an iteration of the algorithm. The rank has been assigned for the evaluated parameters. Finally objective values $J$ for $K_i$, $T_{1i}$ and $T_{3i}$ are updated.

Step 5: Fitness Evaluation

Fitness evaluation is performed after all bees have completed their tours. In this step, the following objective function $J$ is used to evaluate the fitness function
\[ J = \max \left( \min \left( \psi_i \right) \right) \{ i \in \text{set of number of eigenvalues} \} \quad (5.7) \]

Then generate new population for \( K_i, T_{Li} \) and \( T_{3i} \). Here, \( \psi_i \) is the damping ratio.

**Step 6: Global Updating Rule**

Global updating rule is a process used to update the amount of pheromones generated by the bee’s which has constructed the shortest tour from the beginning of the tour. There will be only one bee’s is allowed to update the amount of pheromone which determines the best fitness. The amount of pheromones is updated after all bees have completed their tours.

In this case, the paths belonged to the globally best tour (i.e. the best fitness) of current iteration will receive reinforcement. For the next iteration; the first node of globally best tour in the first iteration will be selected as first node by the each bee.

**Step 7: End Condition**

The algorithm stops the iteration when a maximum number of iterations have been performed. Every tour that was visited by bees should be evaluated. If a better path is discovered in the process, it will be kept for the next reference. The best path selected between all iterations engages the optimal scheduling solution. As a consequence bees never converge to common path. This is observed experimentally, and it is a desirable property. If bees explore different paths then there is a higher probability that one of them will find an improving solution. There are cases where solutions converge to same tour which would make the use the number of bees pointless.
The system is solved for the stabilization of the power system to solve the optimization problem and search for optimal set of PSS parameters, \( \{K_i, T_{1i}, T_{3i}, i = 1, 2, \ldots, n_{PSS}\} \). This ABCMPSS approach provides significant convergence and stabilization for the multi-machine power system.

5.6 EXPERIMENTAL RESULTS

The evaluation of the proposed intelligent algorithms for power system stabilization is presented in this section. The controller parameters \((K_i, T_{1i} \text{ and } T_{3i}, i = 1, 2, \ldots, n_{PSS})\) such as lower bound and upper bound are altered to 0.01 and 50 \((K_i)\) respectively.

5.6.1 Electromechanical Mode Eigenvalues and Damping Ratio

Table 5.1 and 5.2 show the damping ratios, electromechanical mode eigenvalues and optimal PSS parameters of the proposed ABCMPSS and the GAMPSS approaches. It is observed from that the proposed ABCMPSS approach has less damping ratios, electromechanical mode eigenvalues and PSS parameters than GAMPSS approach.

<table>
<thead>
<tr>
<th></th>
<th>GAMPSS</th>
<th>ABCMPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Damping Ratio</strong></td>
<td><strong>Eigenvalue</strong></td>
<td><strong>Damping Ratio</strong></td>
</tr>
<tr>
<td>0.3266</td>
<td>-2.423±j7.012</td>
<td>0.4003</td>
</tr>
<tr>
<td>0.3315</td>
<td>-3.214±j9.147</td>
<td>0.4051</td>
</tr>
<tr>
<td>0.4194</td>
<td>-3.102±j6.714</td>
<td>0.4470</td>
</tr>
<tr>
<td>0.3556</td>
<td>-3.201±j8.414</td>
<td>0.4717</td>
</tr>
</tbody>
</table>
Table 5.2 Optimal PSS Parameters

<table>
<thead>
<tr>
<th></th>
<th>GAMPSS</th>
<th></th>
<th>ABCMPSS</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$K_i$</td>
<td>$T_1$</td>
<td>$T_3$</td>
<td>$K_i$</td>
<td>$T_1$</td>
</tr>
<tr>
<td>0.0028</td>
<td>0.2334</td>
<td>0.2334</td>
<td>0.0035</td>
<td>0.292</td>
</tr>
<tr>
<td>0.0029</td>
<td>0.2334</td>
<td>0.2334</td>
<td>0.0035</td>
<td>0.292</td>
</tr>
<tr>
<td>0.0036</td>
<td>0.2920</td>
<td>0.2920</td>
<td>0.0039</td>
<td>0.369</td>
</tr>
<tr>
<td>0.0031</td>
<td>0.2334</td>
<td>0.2334</td>
<td>0.0032</td>
<td>0.984</td>
</tr>
</tbody>
</table>

5.6.2 Objective Function

Figure 5.5 shows the objective function obtained by the proposed ABCMPSS approach and it is compared with the GAMPSS approach. It is observed from the Figure 5.5 that the convergence of the ABCMPSS takes place in 70 iterations which is better than the GAMPSS approach which takes 100 iterations. It is observed from the Figure 5.5 that the objective function is
decreasing until it attains an optimal value. The optimal value is attained at 70 iterations with the value of -3.51 for the proposed ABCMPSS approach.

For evaluation, the load disturbance of 5% is induced in the considered power system at time 1 second. Then the load disturbance induced power system undergoes stabilization using power system stabilization techniques using the proposed ABCMPSS technique. The controller parameters are adjusted in order to stabilize the system.

5.6.3 System Response under Load Disturbance

5.6.3.1 Load Disturbance of 5%

$\Delta\omega_1$, $\Delta\omega_2$ and $\Delta\omega_3$ deviations that occur in power system because of the introduction of 5% load disturbance are provided in Figures 5.6, 5.7 and 5.8 respectively.

![Figure 5.6 Load Disturbance of 5% in $\Delta\omega_1$](image)
Figure 5.6 depicts the stabilization behavior of the proposed ABCMPSS for optimizing stability parameters under load disturbance of $\Delta \omega_1$. From the figure, it can be observed that initially the system is stable until 1 second, after that the system becomes unstable because of load disturbances. The proposed ABC technique takes only 1.4 seconds for stabilizing the system.

Figure 5.7 represents the stabilization behavior of the proposed ABCMPSS for optimizing stability parameters under load disturbance of $\Delta \omega_2$. The system becomes unstable due to the introduction of $\Delta \omega_2$. The proposed ABCMPSS technique takes only 1.8 seconds for stabilizing the system.

![Figure 5.7 Load Disturbance of 5% in $\Delta \omega_2$](image)

Figure 5.8 represents the stabilization behavior of the proposed ABCMPSS for optimizing stability parameters under load disturbance of $\Delta \omega_2$. The system becomes unstable due to the introduction of $\Delta \omega_2$. The system becomes unstable due to the introduction of $\Delta \omega_2$. The proposed ABCMPSS technique takes only 1.8 seconds for stabilizing the system.
The proposed ABCMPSS technique takes only 1.5 seconds for stabilizing the system.

![Figure 5.8 Load Disturbance of 5% in $\Delta \omega_3$](image)

**5.6.3.2 Load Disturbance of 20%**

This section provides the response of the system for 20% load disturbances. In the previous section, the system response for 5% is analyzed. Since 5% load disturbance is very little, the system response for higher disturbance is analyzed in this section.

$\Delta \omega_1$, $\Delta \omega_2$ and $\Delta \omega_3$ deviations that occur in power system because of the introduction of 20 % load disturbance are discussed in this section. For the 20% load disturbance, on the average, the proposed ABCMPSS approach takes only 2.1 seconds for the convergence.

For the load disturbance of $\Delta \omega_4$, ABCMPSS takes 3.4 seconds for convergence. Similarly, ABCMPSS approach converges in 2.3 seconds for
the load disturbance of $\Delta \omega_2$. For the load disturbance of $\Delta \omega_3$, the time taken for convergence is 2.2 seconds.

Figure 5.9 Load Disturbance of 20% in $\Delta \omega_1$

Figure 5.10 Load Disturbance of 20% in $\Delta \omega_2$
5.6.4 Terminal Voltage Responses

Figures 5.12, 5.13 and 5.14 show the terminal voltage responses for G₁, G₂ and G₃ respectively. From the figures, it can be observed that the utilization of proposed system results in better damping of fluctuations caused in the G₁, G₂ and G₃.

Figure 5.12 represents the terminal voltage response for the G₁ through the proposed ABC approach. Figure 5.12 shows that the voltage fluctuations are damped fairly well through ABC approach in 1.5 seconds.

Figure 5.13 shows terminal voltage response for G₂. Due to the voltage fluctuations, the system becomes unstable after 1 second. Then the proposed ABCMPSS approach damps the voltage fluctuations in 1.4 seconds and the system is stabilized. Similarly, Figure 5.14 shows the terminal voltage response for G₃. For this G₃, the system is stabilized in 1.4 seconds.
Figure 5.12 Terminal Voltage Response of $G_1$

Figure 5.13 Terminal Voltage Response of $G_2$
5.7 SUMMARY

Stabilization of the multi-machine power systems has been one of the most vital research areas in the power system domain. Recently, optimization algorithms have been widely used for the stabilization of the power systems. This proposed approach uses a novel Artificial Bee Colony technique for the power system stabilization. The performance of the proposed approach is compared with the existing GAMPSS approach and it is observed that the proposed ABCMPSS approach provides better performance when compared with the GAMPSS approach in terms of convergence and time taken for stability. The simulation results indicate that the proposed technique results in significant stabilization.