# Diversity Measures in Artificial Bee Colony

Harish Sharma, Jagdish Chand Bansal, and K V Arya

**Abstract** Artificial Bee Colony (ABC) is a recent swarm intelligence based approach to solve nonlinear and complex optimization problems. Exploration and exploitation are the two important characteristics of the swarm based optimization algorithms. Exploration capability of an algorithm is the capability of exploring the solution space to find the possible solution while exploitation capability of an algorithm is the capability of exploiting a particular region of the search space for a better solution. Usually, exploration and exploitation capabilities are contradictory in nature, i.e., a better exploration capability results a worse exploitation capability and vice versa. An economic and efficient algorithm can explore the complete solution space and shows a convergent behavior after a finite number of trials. Exploration and exploitation capabilities, are quantified using various *diversity measures*. In this paper, an analytical study has been carried out for various diversity measures for ABC process.

**Keywords:** Diversity measures, Swarm intelligence, Exploration-Exploitation, Artificial Bee Colony

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# 1 Introduction

Swarm Intelligence has become an emerging and interesting area in the field of nature inspired techniques that is used to solve optimization problems during the past decade. It is based on the collective behavior of social creatures. Swarm based optimization algorithms find solution by collaborative trial and error. Social creatures utilizes their ability of social learning to solve complex tasks. Peer to peer learning behavior of social colonies is the main driving force behind the development of many efficient swarm based optimization algorithms. Researchers have analyzed such behaviors and designed algorithms that can be used to solve nonlinear, non-convex or discrete optimization problems. Previous research [1, 2, 3, 4] have shown that algorithms based on swarm intelligence have great potential to find solutions of real world optimization problems. The algorithms that have emerged in recent years include ant colony optimization (ACO) [1], particle swarm optimization (PSO) [2], bacterial foraging optimization (BFO) [5], artificial bee colony optimization (ABC) [6] etc.

Artificial bee colony (ABC) optimization algorithm introduced by D.Karaboga [6] is a recent addition in this category. This algorithm is inspired by the behavior of honey bees when seeking a quality food source. Like any other population based optimization algorithm, ABC consists of a population of potential solutions. The potential solutions are food sources of honey bees. The fitness is determined in terms of the quality (nectar amount) of the food source. ABC is relatively a simple, fast and population based stochastic search technique in the field of nature inspired algorithms.

There are two fundamental processes which drive the swarm to update in ABC: the variation process, which enables exploring different areas of the search space, and the selection process, which ensures the exploitation of the previous experience. Diversity has a significant effect on the performance of an algorithm [7]. It shows the behavior of the algorithm during the solution search process. A large value of diversity implies exploration of the search space i.e. the algorithm is discovering a true solution in whole search space. A low value of diversity implies exploitation i.e. the algorithm is exploiting a selected search space found during the search process. It is expected that an optimization algorithm retains high diversity value in early stage of the search process and proportionally decreases the value of diversity as search progresses. Study of diversity quantification is important because with this it is possible to rank two or more algorithms in their performance. There are many diversity measures in the literature [7, 8, 9, 10, 11, 12]. A good study on diversity measures for Particle Swarm Optimization process is given in [13]. In this paper, seven important diversity measures have been considered to quantify the diversity of *ABC*. The considered diversity measures have been tested on the five well known benchmark problems to quantify the dispersion of individuals in the swarm of ABC algorithm. Further, effect of outliers has been analyzed over the diversity measures.

Rest of the paper is organized as follows: Section 2 describes brief overview of the basic ABC. Various diversity measures are described in Section 3. In section 4, importance and behavior of diversity measures are discussed. Experimental results are shown in section 5. At last, in section 6, paper is concluded.

## 2 Artificial Bee Colony(ABC) algorithm

The ABC algorithm is relatively recent swarm intelligence based algorithm. The algorithm is inspired by the intelligent food foraging behavior of honey bees. In ABC, each solution of the problem is called food source of honey bees. The fitness is determined in terms of the quality of the food source. In ABC, honey bees are classified into three groups namely employed bees, onlooker bees and scout bees. The number of employed bees are equal to the onlooker bees. The employed bees are the bees which searches the food source and gather the information about the quality of the food source. Onlooker bees which stay in the hive and search the food sources on the basis of the information gathered by the employed bees. The scout bee, searches new food sources randomly in places of the abandoned foods sources. Similar to the other population-based algorithms, ABC solution search process is an iterative process. After, initialization of the ABC parameters and swarm, it requires the repetitive iterations of the three phases namely employed bee phase, onlooker bee phase and scout bee phase. Each of the phase is described as follows:

### 2.1 *Initialization of the swarm*

The parameters for the ABC are the number of food sources, the number trials after which a food source is considered to be abandoned and the termination criteria. In the basic ABC, the number of food sources are equal to the employed bees or onlooker bees. Initially, a uniformly distributed initial swarm of $SN$ food sources where each food source $x_i(i = 1, 2, ..., SN)$ is a $D$-dimensional vector, generated. Here $D$ is the number of variables in the optimization problem and $x_i$ represent the $i^{th}$ food source in the swarm. Each food source is generated as follows:.

$$x_{ij} = x_{minj} + rand[0, 1](x_{maxj} - x_{minj}) \tag{1}$$

where $x_{minj}$ and $x_{maxj}$ are bounds of $x_i$ in $j^{th}$ direction and $rand[0, 1]$ is a uniformly distributed random number in the range [0, 1]

### 2.2 *Employed bee phase*

In employed bee phase, employed bees modify the current solution (food source) based on the information of individual experience and the fitness value of the new solution. If the fitness value of the new solution is higher than that of the old solution, the bee updates her position with the new one and discards the old one. The position update equation for $i^{th}$ candidate in this phase is

$$v_{ij} = x_{ij} + \overbrace{\phi_{ij}(x_{ij} - x_{kj})}^{\text{Step size}} \tag{2}$$

where $k \in \{1,2,...,SN\}$ and $j \in \{1,2,...,D\}$ are randomly chosen indices, $k$ must be different from $i$. $\phi_{ij}$ is a random number between [-1, 1] and component $\phi_{ij}(x_{ij} - x_{kj})$ is the step size of the $i^{th}$ food solution.

## 2.3 Onlooker bees phase

After completion of the employed bees phase, the onlooker bees phase starts. In onlooker bees phase, all the employed bees share the new fitness information (nectar) of the new solutions (food sources) and their position information with the onlooker bees in the hive. Onlooker bees analyze the available information and select a solution with a probability, $prob_i$, related to its fitness. The probability $prob_i$ may be calculated using following expression (there may be some other but must be a function of fitness):

$$prob_i = \frac{fitness_i}{\sum_{i=1}^{SN} fitness_i} \tag{3}$$

where $fitness_i$ is the fitness value of the solution $i$. As in the case of the employed bee, it produces a modification on the position in its memory and checks the fitness of the candidate source. If the fitness is higher than that of the previous one, the bee memorizes the new position and forgets the old one.

## 2.4 Scout bees phase

If the position of a food source is not updated up to predetermined number of cycles, then the food source is assumed to be abandoned and scout bees phase starts. In this phase the bee associated with the abandoned food source becomes scout bee and the food source is replaced by a randomly chosen food source within the search space. In ABC, predetermined number of cycles is a crucial control parameter which is called $limit$ for abandonment.

Assume that the abandoned source is $x_i$. The scout bee replaces this food source by a randomly chosen food source which is generated as follows

$$x_{ij} = x_{minj} + rand[0,1](x_{maxj} - x_{minj}), \text{ for } j \in \{1,2,...,D\} \tag{4}$$

where $x_{minj}$ and $x_{maxj}$ are bounds of $x_i$ in $j^{th}$ direction.

### 2.5 Main steps of the ABC algorithm

Based on the above explanation, it is clear that there are three control parameters in ABC search process: The number of food sources $SN$ (equal to number of onlooker or employed bees), the value of $limit$ and the maximum number of iterations. The pseudo-code of the ABC is shown in Algorithm 1 [14]:

**Algorithm 1** Artificial Bee Colony Algorithm:

```
Initialize the parameters;
while Termination criteria is not satisfied do
    Step 1: Employed bee phase for generating new food sources.
    Step 2: Onlooker bees phase for updating the food sources depending on their nectar amounts.
    Step 3: Scout bee phase for discovering the new food sources in place of abandoned food
    sources.
    Step 4: Memorize the best food source found so far.
end while
Output the best solution found so far.
```

## 3 Diversity Measures

There are many strategies available in the literature for measuring the diversity of swarm. Basically, all the measures are based on the distance metric of individuals. Generally, the diversity measures differ in terms of distance metric or normalization of parameters. Further, the measures are differed based on the choice of swarm center which may be global best solution found so far or may be spatial. In this section, seven different diversity measures, which are based on the Euclidean distance metric, are described. Further, global best swarm center is used in this paper wherever required opposed to a spatial swarm center. Generally, spatial swarm center and global best swarm center can be considered equivalent where the global best is not necessarily centered position in the swarm. Further, for normalization of parameters, the swarm diameter is used, opposed to the radius of swarm.

1. **Swarm Diameter:** The swarm diameter is defined as the distance between two farthest individuals, along any axis [15], of the swarm as shown in Fig. 1. The diameter $D$ is calculated using equation (5):

$$D = \max_{(i \neq j) \in [1, N_p]} \left( \sqrt{\sum_{k=1}^{I} (x_{ik} - x_{jk})^2} \right) \tag{5}$$

   where $N_p$ is the swarm size, $I$ is the dimensionality of the problem and $x_{ik}$ is the $k^{th}$ dimension of the $i^{th}$ individual position.

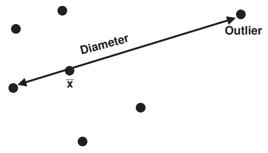


Fig. 1: Swarm Diameter

In Figure 1, an outlier individual is also shown. In a swarm, a significantly deviated individual from the remaining individuals is often termed as *outlier*. From Figure 1, it can be seen that the presence of an outlier can significantly affect the diameter of a swarm.

2. **Swarm Radius:** The radius of a swarm is defined as the distance between the swarm center and the individual in the swarm which is farthest away from it [15], as shown in Fig. 2. The swarm radius is calculated using equation (6):

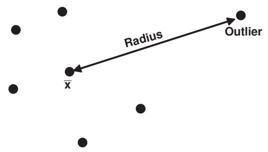


Fig. 2: Swarm Radius

$$R = \max_{i \in [1, N_p]} \left( \sqrt{\sum_{k=1}^{I} (x_{ik} - \bar{x}_k)^2} \right) \tag{6}$$

where the parameters have same meaning as for the swarm diameter. $\bar{x}$ is the position of swarm center and $\bar{x}_k$ represents the $k^{th}$ dimension of $\bar{x}$.
Now, it is evident that the swarm diameter ($D$) and radius ($R$) are two important diversity measures. A large value of $D$ or $R$ exhibits exploration of the search region while low value results exploitation. However, both are badly affected with outliers.

3. **Average Distance around Swarm Center** The average distance from the swarm center $D_A$, can be defined as the average of distances of all individuals from the swarm center. This measure is given in [10] and defined in equation (7)

$$D_A = \frac{1}{N_p} \sum_{i=1}^{N_p} \left( \sqrt{\sum_{k=1}^{I} (x_{ik} - \bar{x}_k)^2} \right) \tag{7}$$

where the notations have their usual meaning. A low value of this measure shows swarm convergence around the swarm center while a high value shows large dispersion of individuals from the swarm center.

4. **Geometric Average Distance around the Swarm Center:** Geometric average is not significantly affected by outliers in the swarm on the high end. The geometric average distance around the swarm center is defined in equation (8).

$$D_{GM} = \left( \prod_{i=1}^{N_p} \sqrt{\sum_{k=1}^{I} (x_{ik} - \bar{x}_k)^2} \right)^{\frac{1}{N_p}} \tag{8}$$

5. **Normalized Average Distance around the Swarm Center:** This diversity measure is almost same as the average distance of all individuals from the swarm center. The only difference is that, the average distance is normalized using the swarm diameter. This normalization can also be done by the radius of the swarm. This diversity measure is given in [15] and described by equation (9):

$$D_N = \frac{1}{N_p \times D} \sum_{i=1}^{N_p} \left( \sqrt{\sum_{k=1}^{I} (x_{ik} - \bar{x}_k)^2} \right) \tag{9}$$

6. **Average of the Average Distance around all Particles in the Swarm:** In this measure, first the average distances, considering each individual as a swarm center are calculated and then an average is taken of all these averaged distances. It is described by equation (10).

$$D_{all} = \frac{1}{N_p} \sum_{i=1}^{N_p} \left( \frac{1}{N_p} \sum_{j=1}^{N_p} \sqrt{\sum_{k=1}^{I} (x_{ik} - x_{jk})^2} \right) \tag{10}$$

This diversity measure shows average dispersion of every individual in the swarm from every other individual in the swarm.

7. **Swarm Coherence:** This diversity measure is given in [9] and described by equation (11):

$$S = \frac{s_c}{\bar{s}} \tag{11}$$

where $s_c$ represents the step size of swarm center which is defined in equation (12):

$$s_c = \frac{1}{N_p} \left\| \sum_{i=1}^{N_p} \tilde{s_i} \right\|_2 \tag{12}$$

where $\tilde{s_i}$ is the vector of step size for $i^{th}$ individual as indicated in equation (2) and $\bar{s}$ shows the average individual step size in the swarm and is defined by equation (13). $||.||_p$ is the Euclidean p-norm.

$$\bar{s} = \frac{1}{N_p} \sum_{i=1}^{N_p} ||\tilde{s_i}||_2 \tag{13}$$

This diversity measure, is calculated by averaging the step sizes of all the individuals in a swarm with respect to swarm center.

The dispersion of the individuals in ABC could be quantified, at some extent, using the various measures of diversity described in this section. The diversity measures shows a trend of exploration or exploitation of the swarm and helps to analyze the behavior of the swarm based algorithms.

## 4 Discussion

Exploration and Exploitation are two important properties of swarm based algorithms. Most of the time, a better exploration capability contradicts a better exploitation capability and vice-versa. In initial iterations, exploration requires to explore the search region and later exploitation is used to thoroughly search the selected search area. Hight value of diversity measure shows the exploration whereas low value exhibits exploitation. A decreasing diversity measures through iterations represents the transition of exploration to exploitation. On the basis of these characteristics, following conclusion have been drawn:

- The swarm diameter presents a required decrease by iterations, as $(x_{ik} - x_{jk})^2$ (refer equation (5)) tends to zero for all the individuals as the swarm converges to a solution. The same behavior is shown by the swarm radius as the distance between each individual to swarm center decreases as the swarm converges with iterations. Further, it is clear from the equations (5) and (6) that the swarm diameter and swarm radius both are very sensitive to the outlier individual. Considering

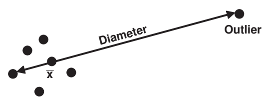


Fig. 3: Swarm Diameter and outlier

  Figure 1 and Figure 3, it can be shown that the diverse behavior of the current swarm shown in Figure 1 and Figure 3 is same, if swarm radius or swarm diameter is the diversity measure, while in Figure 1 the individuals are more diversified than in Figure 3.
- The diversity measure $D_A$, which is shown in equation (7) is robust measure as compared to the swarm diameter and swarm radius because it is based on the average distance of all individuals in the swarm from the swarm center. Hence, this diversity measure is considered less affected due to the outliers as compared to the swarm diameter and swarm radius. But an extreme farthest outlier may skew the individual's dispersion significantly in the swarm. Further, $(x_{ik} - \bar{x}_k)^2 \rightarrow 0$

(refer equation (7)) for all individuals in the swarm as swarm converges. The same behavior is shown by the diversity measure $D_{all}$ given by equation (10) because for all individuals in the swarm, the component $(x_{ik} - x_{jk})^2$ also approaches to zero as swarm converges.

- The diversity measure $D_{GM}$ shown in equation (8) is again a robust measure for measuring diversity. In statistics, geometric average is relatively less affected from outliers.
- The diversity measure $D_N$ shown in equation (9) is the ratio of the average distance $D_A$ and the swarm diameter $D$. Here, diameter is considered as a normalization parameter used to normalize the average distance around the swarm center. In this measure of dispersion, as swarm converges, $D_N$ and $D$, both approaches to zero with iterations. Further, in this dispersion, as the normalization is done by the swarm diameter or the swarm radius, it is significantly influenced by the outlier individuals. Therefore, $D_A$ and $D_{all}$ still may be considered as a better choice for measuring diversity of the swarm.
- The diversity measure $S$, which is shown in equation (11), is the ratio of the absolute step size of the swarm center to the average step size of all individuals in the swarm. A high value of the swarm center step size implies that all the individuals in the swarm are moving in the same direction. Further, a low value implies that a most of the individuals are moving to opposite directions. A high value of average individual's step size in swarm implies the the solutions are significantly changing the positions which implies exploration of the search space while, a low value shows the convergence in the swarm i.e. exploiting the solution search space found so far. Thus, $S$ could be used to analyse the diversity behavior of the algorithm.
  Fig. 4 shows a large swarm diversity and small swarm coherence situation i.e. the individuals are dispersed in the solution search space whereas the step size of swarm center is low relatively.

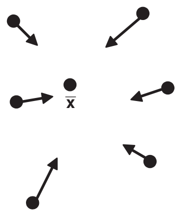


Fig. 4: High Particle Diversity and Small Swarm Coherence

Fig. 5 shows a large swarm diversity with high swarm coherence value i.e. the individuals are dispersed in the solution search space whereas the step size of swarm center is also high.
Further, by analyzing Fig. 6 and Fig. 7, it is clear that the value of $S$ does not depends completely over the diversity of swarm. Therefore, it could be concluded

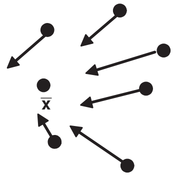


Fig. 5: High Particle Diversity and Large Swarm Coherence

that the swarm coherence is not proportional to swarm diversity of individuals in the ABC and is not a true measure of diversity.

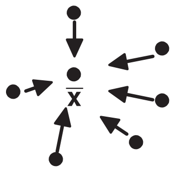


Fig. 6: Low Particle Diversity and Small Swarm Coherence

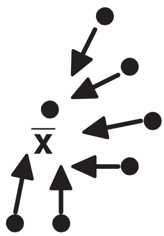


Fig. 7: Low Particle Diversity and Large Swarm Coherence

The outcome of above discussion is that the effect of outlier is significant on most of the diversity measures and it biases the measure of dispersion. However, the effect of outliers could be minimized, it can not be ignored completely.

## 5 Experimental Results

To analyze the various diversity measures for ABC process, experiments have been carried out on five well known benchmark test problems listed in Table 1. For these experiments following experimental setting is adopted:

- Colony size $NP = 50$ [16, 17],
- $\phi_{ij} = rand[-1, 1]$,
- Number of food sources $SN = NP/2$,
- $limit = 1500$ [18, 19],
- The stopping criteria is either maximum number of function evaluations (which is set to be 200000) is reached or the acceptable error (mentioned in Table 1) has been achieved,
- The number of runs =100 and graphs are plotted using the mean of each run.
- Scaling, which is used to constrict the graph outputs to the interval $[0, 1]$, is shown below:

$$\bar{y} = \frac{\bar{y} - \min(\bar{y})}{\max(\bar{y}) - \min(\bar{y})}.$$

This is done to make comparisons of all measures in the same range.

Table 1: Test problems

| **Test Problem** | **Objective function** | **Search Range** | **I** | Acceptable Error |
|---|---|---|---|---|
| Sphere | $f_1(x) = \sum_{i=1}^{I} x_i^2$ | [-5.12 5.12] | 30 | $1.0E-15$ |
| Griewank | $f_3(x) = 1 + \frac{1}{4000}\sum_{i=1}^{I} x_i^2 - \prod_{i=1}^{I}\cos(\frac{x_i}{\sqrt{i}})$ | [-600 600] | 30 | $1.0E-15$ |
| Rosenbrock | $f_4(x) = \sum_{i=1}^{I}(100(x_{i+1} - x_i{}^2)^2 + (x_i - 1)^2)$ | [-30 30] | 30 | $1.0E-15$ |
| Rastrigin | $f_5(x) = 10I + \sum_{i=1}^{I}[x_i^2 - 10\cos(2\pi x_i)]$ | [-5.12 5.12] | 30 | $1.0E-15$ |
| Ackley | $f_6(x) = -20 + e + exp(-\frac{0.2}{I}\sqrt{\sum_{i=1}^{I} x_i{}^3})$ $-exp(\frac{1}{I}\sum_{i=1}^{I}\cos\,(2\pi x_i)x_i)$ | [-1 1] | 30 | $1.0E-15$ |

Figures 8-12 show the swarm diversity, as returned by diversity measure $D$, $R$, $D_A$, $D_{GM}$, $D_N$ and $D_{all}$ with respect to the error of the considered benchmark problems. Figures 13-17 illustrate swarm diversity, as returned by the swarm coherence measure.

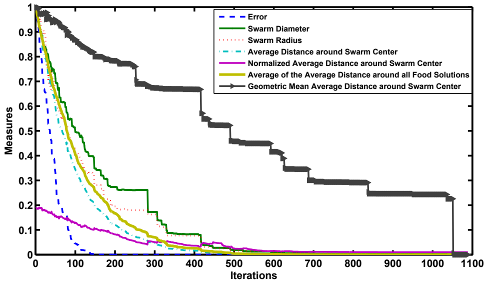


Fig. 8: Diversity Measures with respect to Error on the Spherical Function

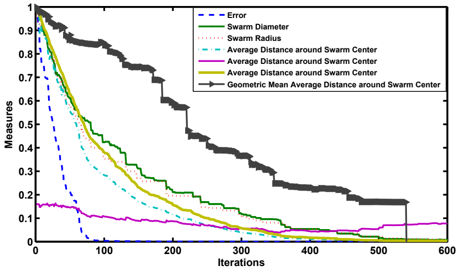


Fig. 9: Diversity Measures with respect to Error on the Griewank Function

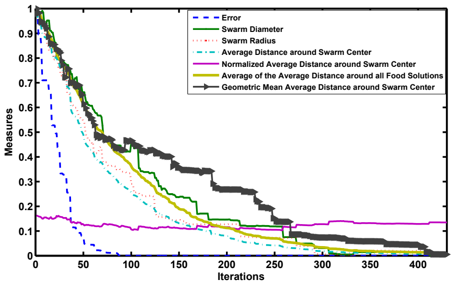


Fig. 10: Diversity Measures with respect to Error on the Rosenbrock Function

## 6 Conclusion

In this paper, various diversity measures are studied and analyzed to measure the dispersion in the swarm of Artificial Bee Colony algorithm (ABC). In swarm based algorithms, diversity measures are used to investigate the exploration and exploita-

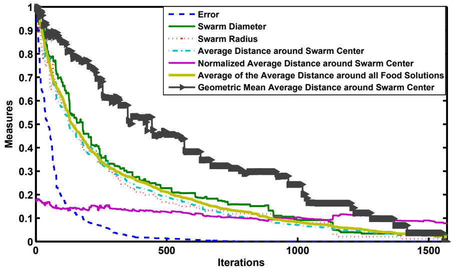


Fig. 11: Diversity Measures with respect to Error on the Rastrigin Function

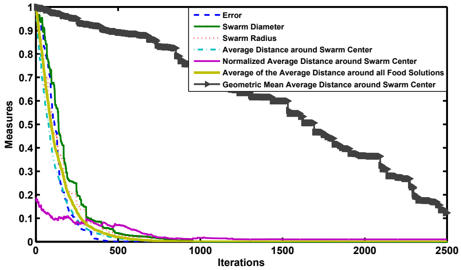


Fig. 12: Diversity Measures with respect to Error on the Ackley Function

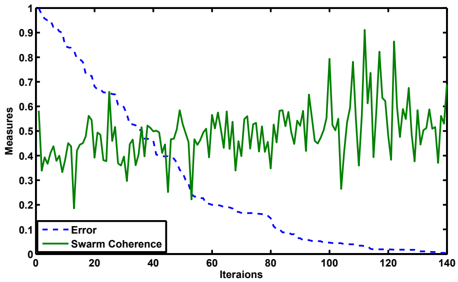


Fig. 13: Swarm Coherence with respect to Error on the Spherical Function

tion characteristics of the algorithms. Further, the diversity measures are analyzed on five well known benchmark problems. The outcome of the experiments shows that the value of diversity measures proportionally decreases with the iterations of the ABC algorithm. A high value of diversity measure shows dispersion in the swarm where as the low value shows convergence of the individuals in the swarm to a solution point. Further, it is found that the diversity measures are more or less effected

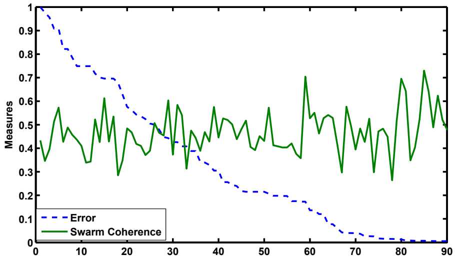


Fig. 14: Swarm Coherence with respect to Error on the Griewank Function

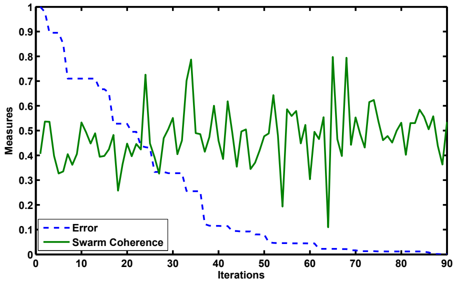


Fig. 15: Swarm Coherence with respect to Error on the Rosenbrock Function

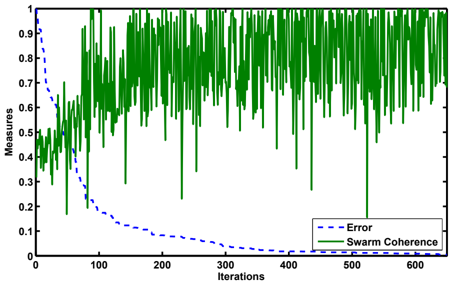


Fig. 16: Swarm Coherence with respect to Error on the Rastrigin Function

by the outliers in the swarm. Diversity measures like the average distance around swarm center, the Geometric Mean average distance around the Swarm Center and the average of average distance around swarm center are less affected by the outliers and could be used for analyzing the exploration and exploitation of the solution search space in the swarm.

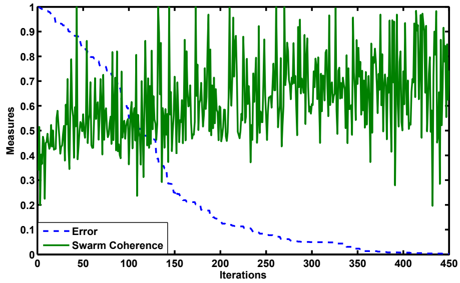


Fig. 17: Swarm Coherence with respect to Error on the Ackley Function

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