

**PARTICLE SWARM OPTIMIZATION  
AND ITS APPLICATION ON  
ANALYSIS OF LOAD FLOW STUDIES**

A PROJECT REPORT  
SUBMITTED IN FULFILLMENT OF THE REQUIREMENTS  
FOR THE AWARD OF THE DEGREE  
OF  
**BACHELOR OF TECHNOLOGY**  
IN  
**ELECTRICAL ENGINEERING**

Submitted By  
**RAJAT SHARMA (2K15/EE/098)**  
**SIDDHARTH MEHROTRA (2K15/EE/125)**  
**TARANG JAIN (2K15/EE/132)**  
**VAIBHAV AHUJA (2K15/EE/134)**

Under the supervision of:

**Professor N.K. Jain**



**DEPARTMENT OF ELECTRICAL ENGINEERING  
DELHI TECHNOLOGICAL UNIVERSITY**  
(Formerly Delhi College of Engineering)  
Bawana Road, Delhi-110042

**MAY 2019**

**DEPARTMENT OF ELECTRICAL ENGINEERING  
DELHI TECHNOLOGICAL UNIVERSITY**

(Formerly Delhi College of Engineering)

Bawana Road, Delhi - 110042

**CANDIDATE'S DECLARATION**

We hereby certify that the work which is presented in the Major Project titled "**PARTICLE SWARM OPTIMIZATION AND ITS APPLICATION ON ANALYSIS OF LOAD FLOW STUDIES**" in fulfillment for the award of the Degree of Bachelor of Technology and submitted to the Department of Electrical Engineering, Delhi Technological University (formerly Delhi College of Engineering), New Delhi is an authentic record of our own, carried out during a period of January 2019 - May 2019, under the supervision of Professor N.K. Jain.

The matter presented in this report has not been submitted by us for the award of any other degree of this or any other Institute/University.

**RAJAT SHARMA**

**2K15/EE/098**

**SIDDHARTH MEHROTRA**

**2K15/EE/125**

**TARANG JAIN**

**2K15/EE/132**

**VAIBHAV AHUJA**

**2K15/EE/134**

Date: 30/05/2019

Place: New Delhi

**DEPARTMENT OF ELECTRICAL ENGINEERING  
DELHI TECHNOLOGICAL UNIVERSITY**

(Formerly Delhi College of Engineering)

Bawana Road, Delhi - 110042

**CERTIFICATE**

This is to certify that the project dissertation titled **PARTICLE SWARM OPTIMIZATION AND ITS APPLICATION ON ANALYSIS OF LOAD FLOW STUDIES** is a bonafide record of the work done under my guidance by

**RAJAT SHARMA** **2K15/EE/098**

**SIDDHARTH MEHROTRA** **2K15/EE/125**

**TARANG JAIN** **2K15/EE/132**

**VAIBHAV AHUJA** **2K15/EE/134**

students of **Delhi Technological University, Delhi** in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology** in **Electrical Engineering**. To the best of my knowledge, this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

It is further certified that the work done in this dissertation is a result of candidates' efforts.

Place: New Delhi  
Date: 30/05/2019

Professor N.K. Jain  
SUPERVISOR  
Department of Electrical Engineering, DTU

## ABSTRACT

Particle Swarm Optimization is an optimization technique that is used to find the minimum or maximum value of a given function and the values of variables or parameters that give this value. With the evolution of computer and the need to incorporate its usage in power system for a more efficient power system management and power system stability, this intelligent optimization technique is finding deeper roots in scholars' and electrical engineers' field of study.

In this project, Particle Swarm Optimization Technique is first implemented on Rosenbrock Function (Lab Model) and then implemented on 5-Bus Power System (Practical Model). Particle Swarm Optimization technique is used in Load Flow Analysis to find the unknown variables of voltage, power angle, load and generation of buses using the known values of buses in power system as parameters. Here, voltage and power angle of buses form the parameters. These parameters are used to calculate active and reactive power of each bus which is compared with the known active and reactive power of buses of the system. The mismatch between the two forms the objective function which is optimized by Particle Swarm Optimization technique finally giving us the unknown values.

This work also tries to make the technique more efficient. The higher efficiency is obtained by reducing the number of iterations ie. total time taken for program to give the result. Before particles reach their final value, they undergo a large number of variations. The particles, after a certain number of iterations, are repositioned such that they are close to final solution. The variations are thus reduced, iterations reduced and program's efficiency increases.

## **ACKNOWLEDGEMENT**

On the very outset of this report, we would like to extend our sincere and heartfelt obligation towards all the people who have helped us in this endeavour.

We are ineffably indebted to **Professor N.K Jain** for his conscientious guidance, exceptional mentoring and constant monitoring to accomplish this assignment.

We would also like to extend our sincere gratitude to the **Department of Electrical Engineering**, for giving us the opportunity to execute this project, which is an integral part of the curriculum in B.Tech program at Delhi Technological University.

**RAJAT SHARMA (2K15/EE/098)**

**SIDDHARTH MEHROTRA (2K15/EE/125)**

**TARANG JAIN (2K15/EE/132)**

**VAIBHAV AHUJA (2K15/EE/134)**

# TABLE OF CONTENTS

Title	Page No.
<b>ABSTRACT</b> . . . . .	iii
<b>ACKNOWLEDGEMENT</b> . . . . .	iv
<b>TABLE OF CONTENTS</b> . . . . .	v
<b>LIST OF TABLES</b> . . . . .	vii
<b>LIST OF FIGURES</b> . . . . .	viii
<b>1 Introduction</b> . . . . .	1
1.1 Evolutionary Algorithms . . . . .	1
1.2 Particle Swarm Optimization . . . . .	2
1.3 Basic Particle Swarm Optimization Algorithm . . . . .	2
1.3.1 Inertia Weight . . . . .	3
1.3.2 Acceleration constants $C_p$ and $C_g$ . . . . .	5
1.3.3 Random numbers $R_p$ and $R_g$ . . . . .	5
<b>2 Laboratory Application of PSO</b> . . . . .	8
2.1 RosenBrock Function . . . . .	8
2.2 Analysis Of Results . . . . .	9
2.2.1 Analysis of Results with Variation in Random Variables and Acceleration Constants . . . . .	9
<b>3 Improvements in PSO</b> . . . . .	13
3.1 Constant Inertia . . . . .	13
3.2 Positional Weightage PSO . . . . .	13
3.3 Graphical Visualization of Trajectory of Different Particles	16
3.4 Conclusion . . . . .	26

<b>4 Analysis of Load Flow Studies using PSO: Field Application</b>	<b>27</b>
4.1 Analysis for Load Flow Studies . . . . .	27
4.2 Implementation Details . . . . .	31
4.2.1 Output . . . . .	33
<b>5 Improvement in PSO applied to Load Flow Studies</b> . . . . .	<b>39</b>
5.1 Positional Weightage PSO in Load Flow . . . . .	39
5.2 Output . . . . .	42
5.3 Conclusion . . . . .	48
<b>6 APPENDIX</b> . . . . .	<b>49</b>

# List of Tables

2.1 VARIATION OF RESULT ACCORDING TO $R_g$ BY KEEP- ING $R_p = 0.2$ . . . . .	9
2.2 VARIATION OF RESULT ACCORDING TO $R_g$ BY KEEP- ING $R_p = 0.4$ . . . . .	10
2.3 VARIATION OF RESULT ACCORDING TO $R_g$ BY KEEP- ING $R_p = 0.6$ . . . . .	11
2.4 EFFECT OF VARIATION OF PARAMETERS ON CON- VERGENCE TIME IN TERMS OF FUNCTION EVALU- ATIONS . . . . .	12
3.1 COMPARISION OF RESULTS OBTAINED FROM DIF- FERENT METHODS . . . . .	15
4.1 PSO Loadflow Analysis . . . . .	33
4.2 Line Flow and Losses . . . . .	33
5.1 PSO Loadflow Analysis using Improved PSO . . . . .	42
5.2 Line Flow and Losses . . . . .	42
5.3 VARIATON OF PARAMETERS WITH DIFFERENT VAL- UES OF LIMIT AND S1 . . . . .	47

# List of Figures

1.1 Flowchart of PSO Algorithm . . . . .	6
2.1 Graphical representation of Rosenbrock function . . . . .	8
3.1 Flowchart for Positional Weightage Algorithm . . . . .	14
3.2 COMPARISON BETWEEN THE NORMAL AND THE POSITIONAL WEIGHTED PSO. . . . .	15
3.3 Particle 1 . . . . .	16
3.4 Particle 2 . . . . .	17
3.5 Particle 3 . . . . .	18
3.6 Particle 4 . . . . .	19
3.7 Particle 5 . . . . .	20
3.8 Particle 6 . . . . .	21
3.9 Particle 7 . . . . .	22
3.10 Particle 8 . . . . .	23
3.11 Particle 9 . . . . .	24
3.12 Particle 10 . . . . .	25
4.1 Loadflow methods . . . . .	30
4.2 Loadflow methods . . . . .	32
4.3 OBJECTIVE FUNCTION V/S ITERATIONS . . . . .	34
4.4 THETA BUS 2 V/S ITERATIONS . . . . .	35
4.5 VOLTAGE BUS 2 V/S ITERATIONS . . . . .	35
4.6 THETA BUS 3 V/S ITERATIONS . . . . .	36
4.7 THETA BUS 4 V/S ITERATIONS . . . . .	36
4.8 VOLTAGE BUS 4 V/S ITERATIONS . . . . .	37
4.9 THETA BUS 5 V/S ITERATIONS . . . . .	37
4.10 VOLTAGE BUS 5 V/S ITERATIONS . . . . .	38
5.1 Flowchart for the process . . . . .	41

5.2	GRAPH FUNCTION IMPROVED PSO V/S ITERATIONS	43
5.3	THETA BUS 2 V/S ITERATIONS . . . . .	43
5.4	VOLTAGE BUS 2 V/S ITERATIONS . . . . .	44
5.5	THETA BUS 3 V/S ITERATIONS . . . . .	44
5.6	THETA BUS 4 V/S ITERATIONS . . . . .	45
5.7	VOLTAGE BUS 4 V/S ITERATIONS . . . . .	45
5.8	THETA BUS 5 V/S ITERATIONS . . . . .	46
5.9	VOLTAGE BUS 5 V/S ITERATIONS . . . . .	46
5.10	COMPARISION OF KOUNT VALUE OBTAINED IN IMPROVED PSO AND NORMAL PSO . . . . .	47

# CHAPTER 1

## Introduction

---

### 1.1 Evolutionary Algorithms

Recently, scientific and technological advancements have led to the invention of new techniques based on evolution which are fast becoming a noteworthy analysis field. It's not solely attributable to its effectiveness in searching for the correct solution but also to its close resemblance to natural social paradigms. Since it's influenced by nature, these methods are supported by biological evolution. The basic idea and main features of EAs are represented as a contest between a populations of people. The main characteristics of EAs are as follows: They deal with an entire group of candidate solutions at the same time i.e., EAs are population-based. EAs largely use recombination to combine data that is obtained from a huge variety of candidate answers into a brand new solution. These optimisation tools also incorporate a degree of randomness into their working algorithm.

Kennedy, a social scientist, and Eberhart, an electrical engineer, conceptualized the idea of particle swarms, to build computational intelligence capabilities, making use of the prevailing systems that interact naturally. The primary simulations were inspired by social functioning of concerned analogues of flocks of birds looking for food. This led to the development of a robust optimization method; Particle Swarm optimization (PSO). PSO tries to imitate the goal-oriented working procedure of swarms that can be viewed biologically.

## 1.2 Particle Swarm Optimization

In the PSO calculation, the group of particles in the search area intend to efficiently solve a fitness problem, trying to emulate a path like the movement of a flock of birds in indigenous surroundings unconsciously using this technique in food search. The particles start assessing their quality or wellness at a particular position as soon as they are put arbitrarily in the search space. At that point, every particle moves to a brand new location which produces a more preferable fitness over the past position. This movement relies on the history of particles personal best and current locations with those of the best and most effective positions achieved by different particles in the swarm, with some arbitrary fluctuations. Consequently, in ensuing iterations, the swarm accomplishes the most ideal answer for the function representing the fitness, with a particular number of particles cooperating with each other. The function that is to be optimized in the PSO algorithm is an exhibition assessment criterion that relies upon the application territory of the calculation. The mathematical definition typically outlines the performance basis to measure the framework execution accomplished through an exhibition list. Continuous and rigorous advancement as it happens in nature, spurs the genetic evaluation methodology and other populace based pursuit strategies. However, PSO, unlike most different strategies, depends on analogies with social conduct of creatures and fowls. Selection task is not at all involved in PSO calculation and in this way, the hunt procedure holds every one of the swarm particles throughout the operation. The position and speed of every one of the particles is refreshed in each iteration, as per the particles own claim and group's best positions achieved till that point of time. Consequently, in contrast to other developmental techniques, PSO never actualizes the arrangement of the survival of the fittest theory.

## 1.3 Basic Particle Swarm Optimization Algorithm

This calculation comprises of  $n$  particles which make up a swarm, along with every particle's position showing a potential answer to the  $d$  dimensional search area and its fitness function whose value is variably optimised. The particle updates its location affected by essentially three ele-

ments:

- The self inertia
- Most optimal solution of the particle itself
- Most optimal global solution of the swarm

$$v_{i,d} = \omega v_{i,d} + c_p r_p(p_{i,d} - x_{i,d}) + c_g r_g(g_d - x_{i,d})$$

$$x_i = x_i + v_i$$

Where  $\omega$  is the inertia of particle  $i$  in the  $d$  dimension  $c_p$  and  $c_g$  are acceleration constants.  $r_p$  and  $r_g$  are random values in the range  $[0, 1]$ .  $p_{i,d}$  speaks to the individual best position of the  $i^{th}$  molecule and  $g_d$  speaks to the worldwide best position.

$x_{i,d}$  give the present position of the  $i^{th}$  particle in the  $d^{th}$  dimension. The velocity updation statement in PSO comprises of 3 sections:

**Momentum:** It shows the propensity of the particle to manoeuvre in a similar way as it was going in the past cycle. It appends the impact of the past velocity on present speed of the particle.

**Cognitive part:** It shows the affinity of the particle's velocity towards its own best location (pbest). Alluded to as "memory", "self-information" or "recognition".

**Social part:** It constitutes the effect of the swarm's best position ( $g_{best}$ ) obtained till that time on the current velocity. Also known as "collaboration", "social learning" or "shared data".

### 1.3.1 Inertia Weight

Particle's velocity on each dimension depends on a most extreme values in the search space, Vmax. This highest speed decides the goals or purpose with which areas between the current position and the objective position (best up until now) can be dealt with. The utilization of hard limits introduces a few issues. For example in the event that Vmax is excessively high,

at that point particles may disappear from some important areas ,and on the off chance that Vmax is excessively low, at that point some good locations will be unreachable. Accordingly so as to lessen the significance of Vmax, and to hone the searching capacity of particles, a weight term is added to the PSOs conditions. This is called inertia weight ( $\omega$ ) and it controls the impact which the previous iteration velocity has on the present value. Bigger estimation of  $\omega$  improves worldwide hunt ability and the partial search capacity of PSO technique is improved by lesser value of  $\omega$ . By and large, it is equivalent to 1, however in the end the inquiry capacity diminishes and the particles stall out at a non-ideal area. In experimental work,  $w$  is kept in the middle of 0.9 to 0.4 and the values are linearly decreased so the calculation enables the particles to investigate more extensive regions in starting and adjacent regions in later stages with decreased rates. This setting gives a more noteworthy probability of achieving the objective ideal position rapidly. In the event that we translate:

$$c_p r_p(p_i, d - x_{i,d}) + c_g r_g(g_d - x_i, d)$$

as the external power  $f_i$ , that the particle encounters, at that point the adjustment in a particle's speed (i.e., the acceleration gained by the particle) can be composed as;

$$\Delta v_i = f_i(1 - \omega)v_i v_i = f_i - (1 - \omega)v_i$$

The component  $1 - \omega$  acts adequately as a contact coefficient. Thus  $\omega$  is said to be the ease of movement (fluidity) of the medium wherein a particle moves. Along these lines the best execution is obtained by setting  $\omega$  at first to some generally high number (e.g., 0.9).the higher influence of  $\omega$  relates to a framework where particles move in a medium with low viscoity and perform broad investigation. At the point when  $\omega$  is slowly decreased to a much lower number (e.g., 0.4), the framework turns out to be increasingly exploitative and dissipative and would be better at homing into nearby optima. It is also conceivable to begin from estimations of  $\omega > 1$ , however the swarm will become insecure and doddery until and except if the value is diminished adequately to acquire the swarm a steady location

### **1.3.2 Acceleration constants $C_p$ and $C_g$**

These constants are associated with the speed with which the particles fly to the most optimal position of swarm and its very own best position. They control the distance and time spent by particle to achieve the most ideal position. These constants must be appropriately chosen to ensure that the particle lands in a right position. For too huge an estimation of these constants, the right position may get bypassed by the particle and for too little a value, the particle almost certainly not achieve the objective position. By and large every one of these constants are kept at the numerical value of 2 to make the iterations taken to manoeuvre towards the swarm's global best and the particle's own best as equivalent and total time is halved. These constants give the weighing of these terms towards Gbest and Pbest areas.

### **1.3.3 Random numbers $R_p$ and $R_g$**

The draw on the particles towards Gbest and Pbest locations are managed by including arbitrary numbers in the update rules. These are irregular fictitiously defined values and decide the magnitude of arbitrary powers towards the 2 most optimal positions. A random segment is added to the PSO calculation by them and they help keep the calculation from stalling out at a non-ideal nearby least or greatest arrangement.

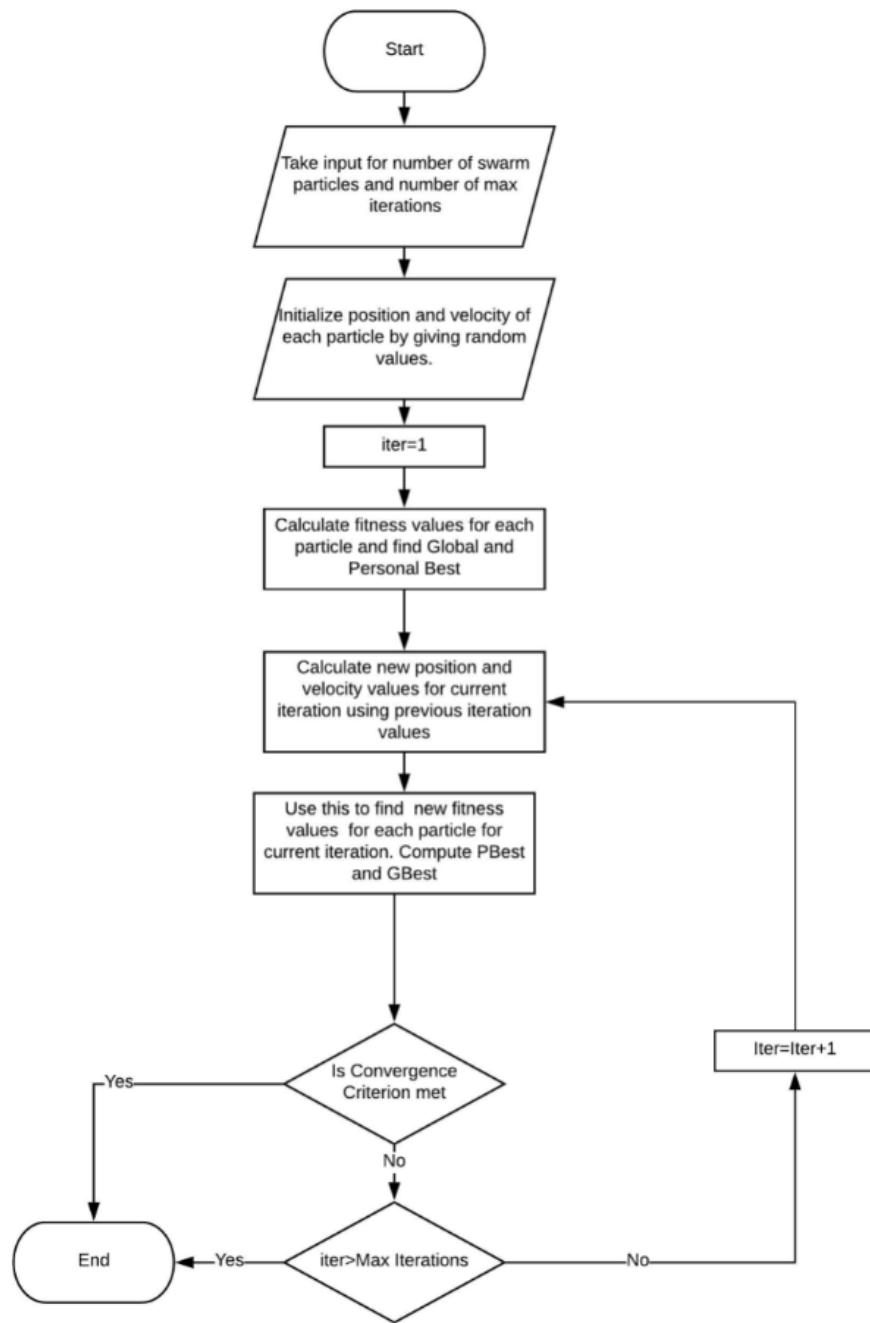


Figure 1.1: Flowchart of PSO Algorithm

## Advantages

- PSO calculation does not include selection activity or transformation calculation.
- The hunt can be done by changing the particle's speed over and over again. By gaining valuable insights from group's location and position history, particles fly only to great regions (where there is a high plausibility of discovering food).

- PSO depends on artificial intelligence and thus, can be used in both logical engineering operations and research as well as scientific and technological applications.
- Simple estimations are associated with PSO calculation and with the advancement of more up to date assessment methods, they are done easily and inn a lot less time.

### **Disadvantages**

- Standard PSO experiences a significant increase in the complexity of search operations with even a slight increase in the dimension or size of search space.
- The technique is defenceless against fractional confidence in the operation, which prompts a considerably less exact guideline of its speed and the direction.
- Due to the absence of dimensionality this strategy can't be utilized for analysis of the non-coordinate framework, for example, the problem pertaining to the energy field and the moving principles of the particles in this field.

# CHAPTER 2

## Laboratory Application of PSO

---

### 2.1 RosenBrock Function

The Particle Swarm Optimization Algorithm was used to find the minimum value of the Rosenbrock function.

In mathematical optimization, the Rosenbrock function is a non-convex function, which is applied as a performance test problem for optimization algorithms. It is also known as Rosenbrock's valley or Rosenbrock's banana function.

The global minimum is inside a long, narrow, parabolic shaped flat valley. To find the valley is trivial. The function is defined by

$$f(x, y) = (1 - x)^2 + 100(y - x^2)^2$$

It has a global minimum at  $(x, y) = (1, 1)$  where  $f(x, y) = 0$ .

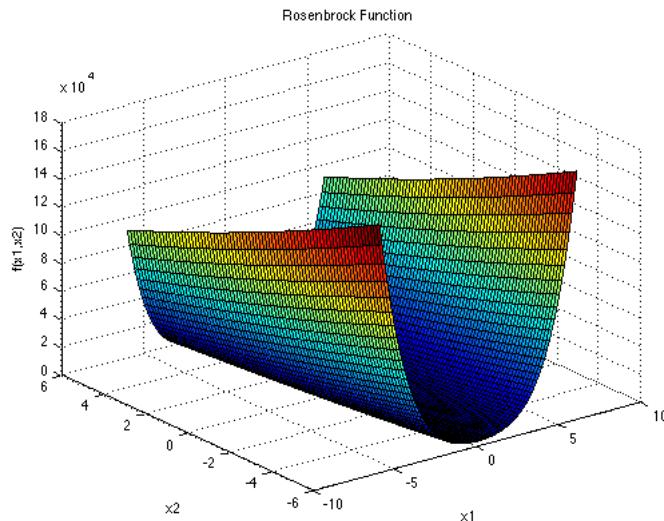


Figure 2.1: Graphical representation of Rosenbrock function

The MATLAB code for the implementation of PSO algorithm has been given in the appendix at the end. The results obtained were then analysed on the basis of variation in the various parameters.

## 2.2 Analysis Of Results

### 2.2.1 Analysis of Results with Variation in Random Variables and Acceleration Constants

#### Effect of variation of parameters on Results:

- Number of particles = 10
- Iterations=100
- Tolerance= $10^{-4}$
- $C_p = 2$
- $C_g = 2$

$R_g$	$n$	$x_1$	$x_2$	$f_{min}$
0.1	51	1.000017	1.000041	$6.779 \times 10^{-9}$
0.2	55	0.810600	0.655274	$3.61 \times 10^{-2}$
0.3	50	0.780632	0.607469	$4.849 \times 10^{-2}$
0.4	50	0.913663	0.834657	$7.45 \times 10^{-3}$
0.5	53	0.889621	0.790527	$1.23 \times 10^{-2}$
0.6	58	0.752368	0.565055	$6.14 \times 10^{-2}$
0.7	51	0.979989	0.960116	$4.073 \times 10^{-4}$
0.8	55	0.858121	0.736081	$2.01 \times 10^{-2}$
0.9	59	0.801204	0.640638	$3.968 \times 10^{-2}$
1.0	56	0.933261	0.870666	$4.463 \times 10^{-3}$

Table 2.1: VARIATION OF RESULT ACCORDING TO  $R_g$  BY KEEPING  $R_p = 0.2$

**Observation:** According to the above table we observe that when we kept the value of  $R_p = 0.2$  and varied the value of  $R_g$ , the most optimum solution is obtained at  $R_g = 0.1$  after 51 iterations; i.e.  $6.779 \times 10^{-9}$ . Whereas for the other values of  $R_g$ , we obtain vague values as result.

- Number of particles = 10
- Iterations=100
- Tolerance= $10^{-4}$
- $C_p = 2$
- $C_g = 2$

$R_g$	$n$	$x_1$	$x_2$	$f_{min}$
0.1	54	0.821723	0.673536	$3.204 \times 10^{-2}$
0.2	38	0.860219	0.384371	$1.977 \times 10^{-2}$
0.3	46	0.851775	0.724470	$2.209 \times 10^{-2}$
0.4	50	0.896989	0.803815	$1.061 \times 10^{-2}$
0.5	55	0.833493	0.692122	$2.839 \times 10^{-2}$
0.6	43	0.834538	0.695015	$2.758 \times 10^{-2}$
<b>0.7</b>	<b>54</b>	<b>1.00011</b>	<b>1.00002</b>	<b><math>1.208 \times 10^{-10}</math></b>
0.8	53	0.999992	0.999982	$4.189 \times 10^{-10}$
0.9	47	1.000200	1.000405	$4.393 \times 10^{-5}$
1.0	60	1.000916	1.001883	$1.095 \times 10^{-6}$

Table 2.2: VARIATION OF RESULT ACCORDING TO  $R_g$  BY KEEPING  $R_p = 0.4$

**Observation:** According to the above table we observe that when we kept the value of  $R_p = 0.4$  and varied the value of  $R_g$ , the most optimum solution is obtained at  $R_g = 0.7$  after 54 iterations; i.e.  $1.028 \times 10^{-10}$ . Whereas for the other values of  $R_g$ , we obtain vague values as result.

- Number of particles = 10
- Iterations=100
- Tolerance= $10^{-4}$
- $C_p = 2$
- $C_g = 2$

$R_g$	$n$	$x_1$	$x_2$	$f_{min}$
0.1	55	0.768956	0.588862	$5.397 \times 10^{-2}$
0.2	50	0.892328	0.795982	$1.161 \times 10^{-2}$
0.3	53	0.827069	0.682662	$3.01 \times 10^{-2}$
0.4	47	0.956819	0.914889	$1.903 \times 10^{-3}$
<b>0.5</b>	<b>51</b>	<b>1.00045</b>	<b>1.00088</b>	<b><math>2.436 \times 10^{-7}</math></b>
0.6	58	0.999475	0.998774	$3.377 \times 10^{-6}$
0.7	55	0.999511	0.999031	$2.491 \times 10^{-7}$
0.8	57	0.999688	0.999465	$8.895 \times 10^{-7}$
0.9	55	1.000291	1.000526	$3.977 \times 10^{-7}$
1.0	100	1.001326	1.002635	$1.792 \times 10^{-6}$

Table 2.3: VARIATION OF RESULT ACCORDING TO  $R_g$  BY KEEPING  $R_p = 0.6$

**Observation:** According to the above table we observe that when we kept the value of  $R_p = 0.6$  and varied the value of  $R_g$ , the most optimum solution is obtained at  $R_g = 0.5$  after 51 iterations; i.e.  $2.436 \times 10^{-7}$ . Whereas for the other values of  $R_g$ , we obtain vague values as result.

**The highlighted set of observations represent the best and minimum value of the Rosenbrock obtained at the corresponding values of the random variables and independent variables  $x_1$  and  $x_2$ .**

- Number of particles = 10
- Iterations=100
- Tolerance= $10^{-4}$
- $C_p = 2$
- $C_g = 2$

$R_p$	$R_g$	$n$	$x_1$	$x_2$	$Kount$	$f_{min}$
<b>0.2</b>	<b>0.1</b>	<b>51</b>	<b>1.000017</b>	<b>1.000041</b>	<b>1031</b>	<b><math>6.779 \times 10^{-9}</math></b>
0.4	0.7	54	1.00011	1.00002	1091	$1.208 \times 10^{-10}$
0.6	0.5	51	1.00045	1.00088	1031	$2.436 \times 10^{-7}$

Table 2.4: EFFECT OF VARIATION OF PARAMETERS ON CONVERGENCE TIME IN TERMS OF FUNCTION EVALUATIONS

**Observation:** Thus by analysing different pairs of  $R_g$  and  $R_p$  we observe that we get the most optimum solution at  $R_p = 0.4$  and  $R_g = 0.7$ . Although the convergence time in this case(1091) is greater than others(1031), we can compromise with it since we are focused on getting better solution.

# CHAPTER 3

---

## Improvements in PSO

### 3.1 Constant Inertia

Here, after comparing the results obtained by keeping different values of inertia i.e. constant weight, we chose the one which gave us the optimum solution. The optimum value was found to be at  $\omega = 0.6$ .

The code has been given in Appendix at the end for reference.

### 3.2 Positional Weightage PSO

From the previous methods, we could see that before the particle swarm approached the true solutions, each individual particle made a high number of vibrations, i.e. the particle's value oscillated about the true solutions before the particle finally converged there.

We also know that in order to make the PSO program more efficient, we have to reduce the number of iterations.

Thus, in order to achieve this, we aim to reduce the vibrations. These can be reduced if all the particles were repositioned after some time, so that each particle was closer to true solution. This reduces the vibrations of each individual particle as well as the effect of one particle on others that caused others to stray away from true solution..

The algorithm followed is:

1. Let program run normally till a fixed number of iterations. (Say 14)
2. or each particle, take into account the value that each particle gives throughout these 14 iterations. Assign weight to each position depending upon the value and kind of solution we need(Maxima/minima). Higher the weight,

better will be the position.

3. Finally, take the weighted mean and continue the program to run as normal.

This approach not only reduces the vibrations, but also prevents a possible solution part of the function, that in normal case might be left out or be reached after longer time, to be taken into account.

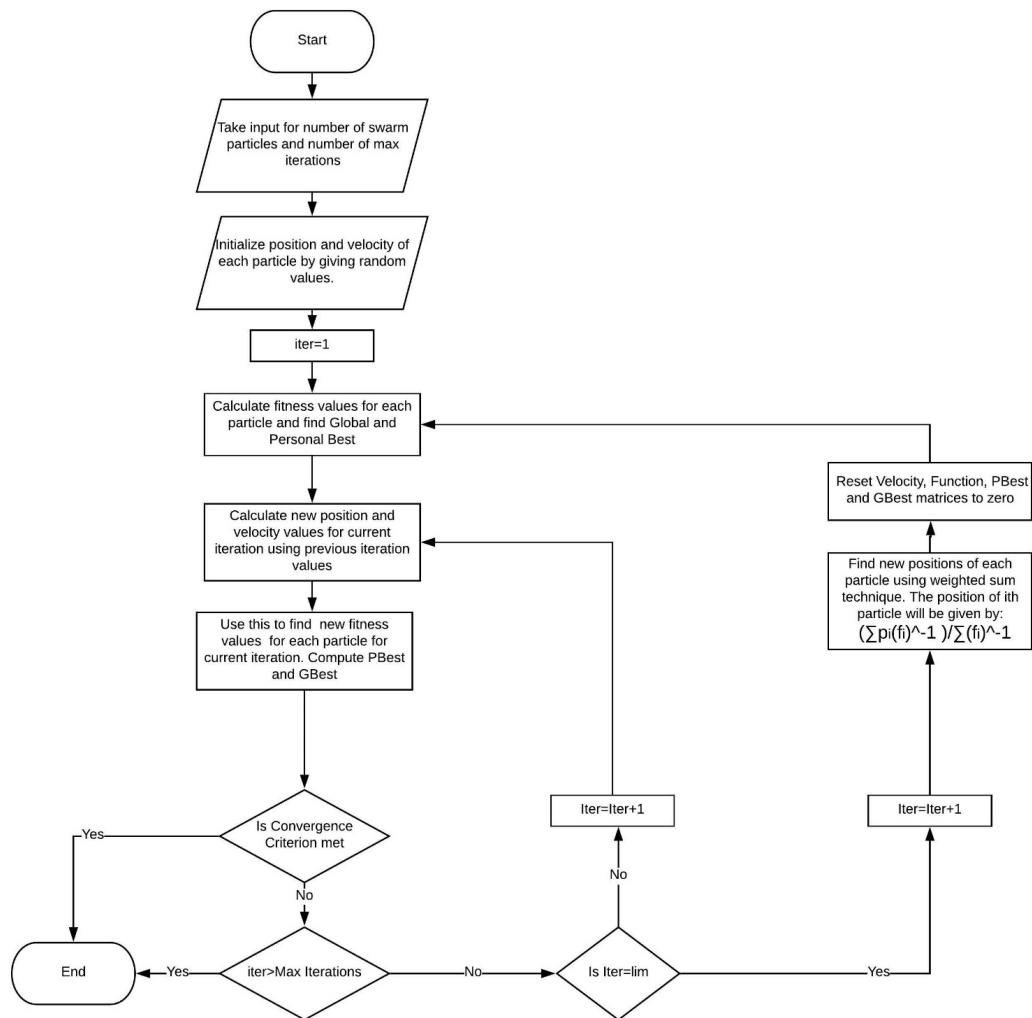


Figure 3.1: Flowchart for Positional Weightage Algorithm

$x_1$	$x_2$	$F$	$It$	Kount	Nomenclature
0.9603553	0.9209168	0.001758157	41	831	Normal
0.9999969	0.9999972	1.17099*10-9	34	691	Constant Inertia
1.000843	1.001637	9.47243*10-7	23	481	Positional weightage PSO

Table 3.1: COMPARISION OF RESULTS OBTAINED FROM DIFFERENT METHODS

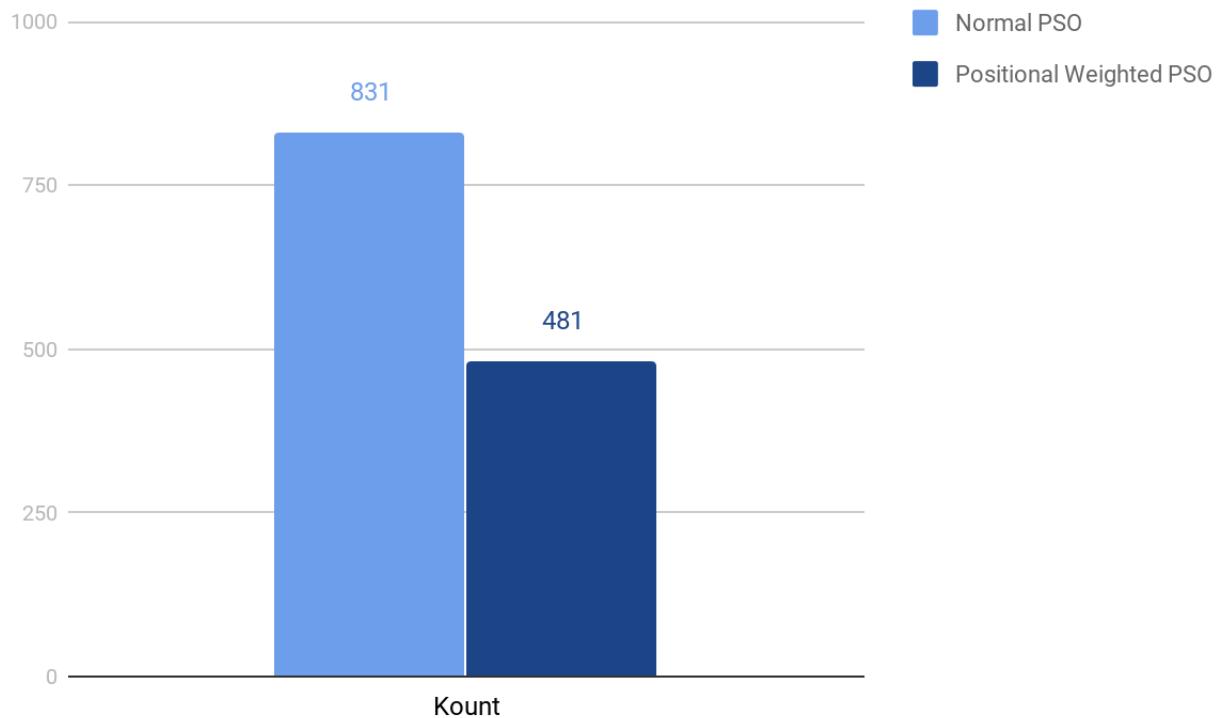


Figure 3.2: COMPARISON BETWEEN THE NORMAL AND THE POSITIONAL WEIGHTED PSO.

### 3.3 Graphical Visualization of Trajectory of Different Particles

The trajectory of each particle before finally converging to a minimum value is depicted along with vibrations in the results obtained for the function with the number of iterations for all the 3 methods. The first two graphs in each particle are for normal and fixed inertia methods and the subsequent ones denote the positional weighted average method.

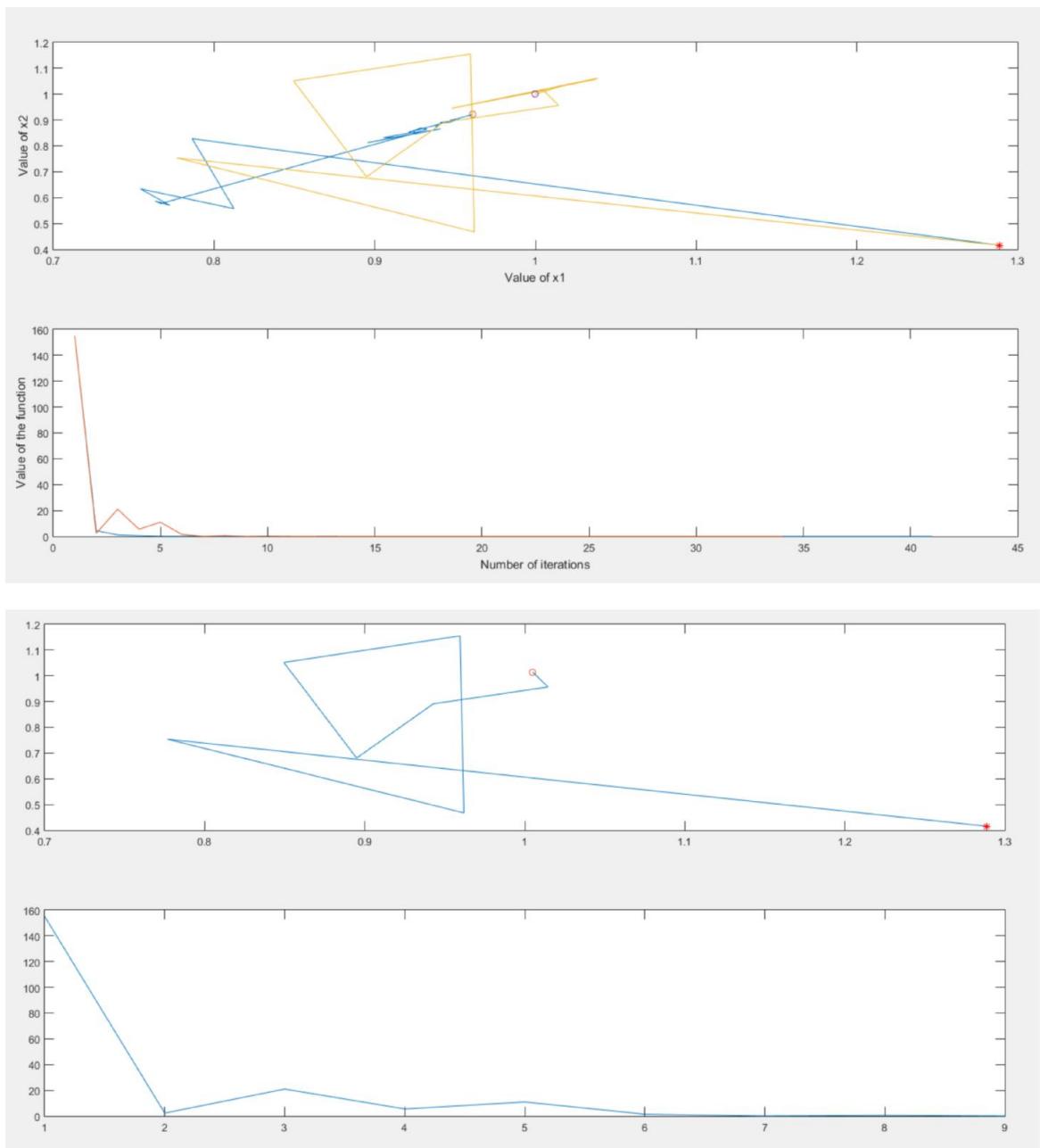


Figure 3.3: Particle 1

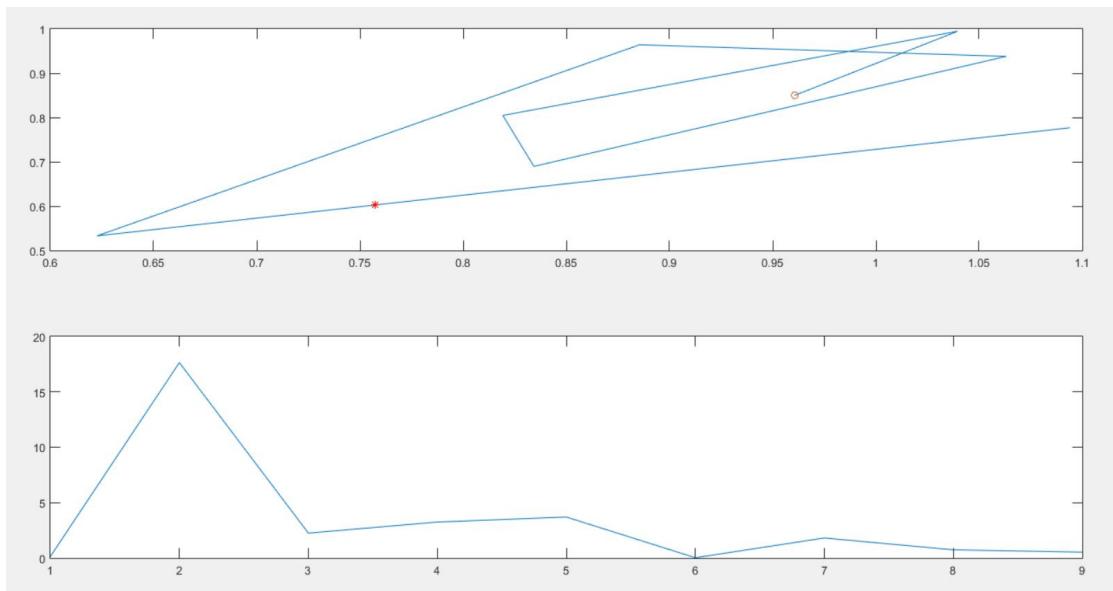
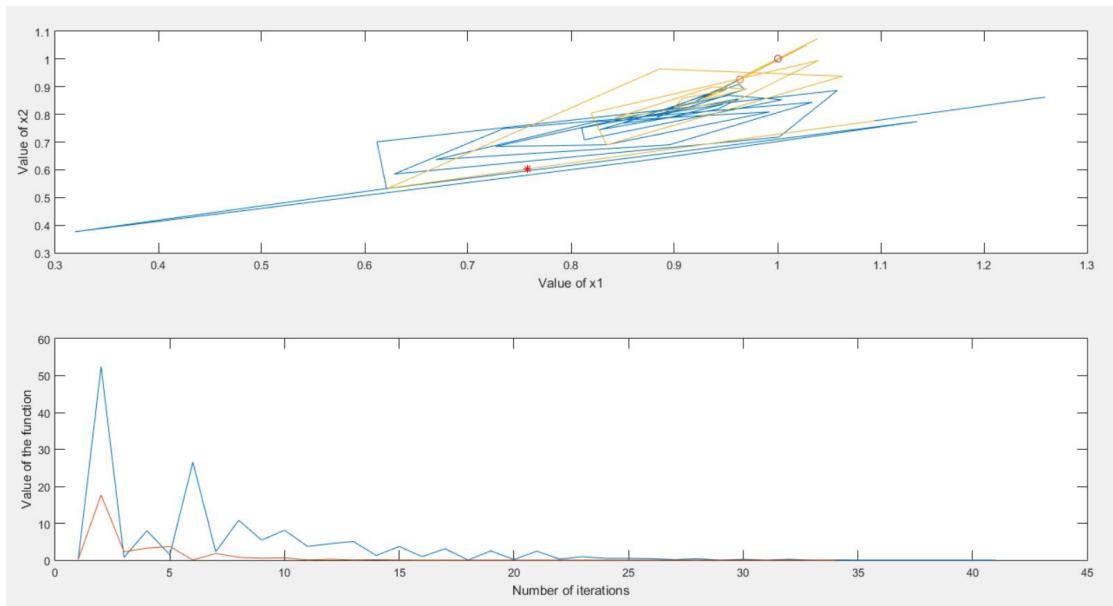


Figure 3.4: Particle 2

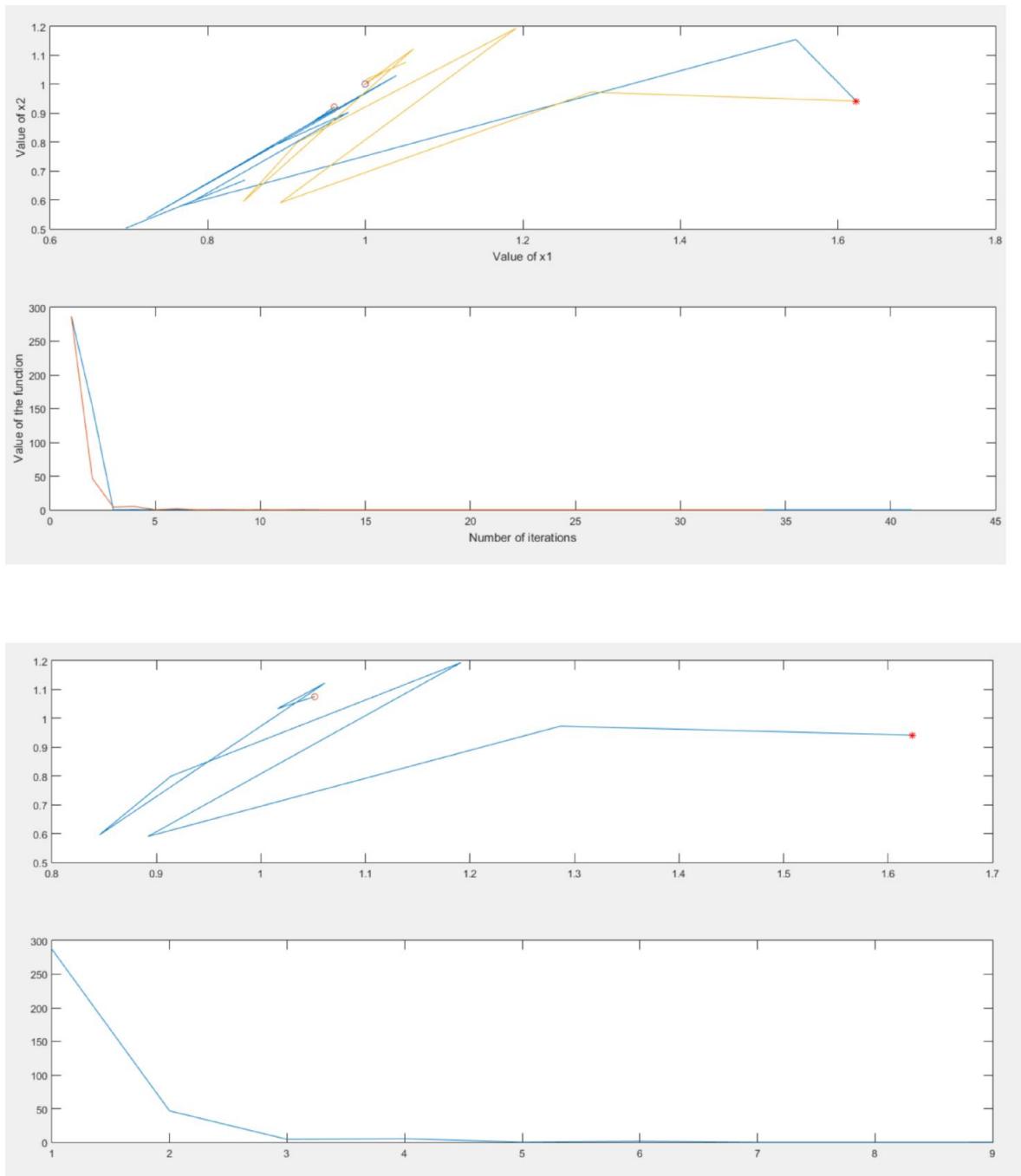


Figure 3.5: Particle 3

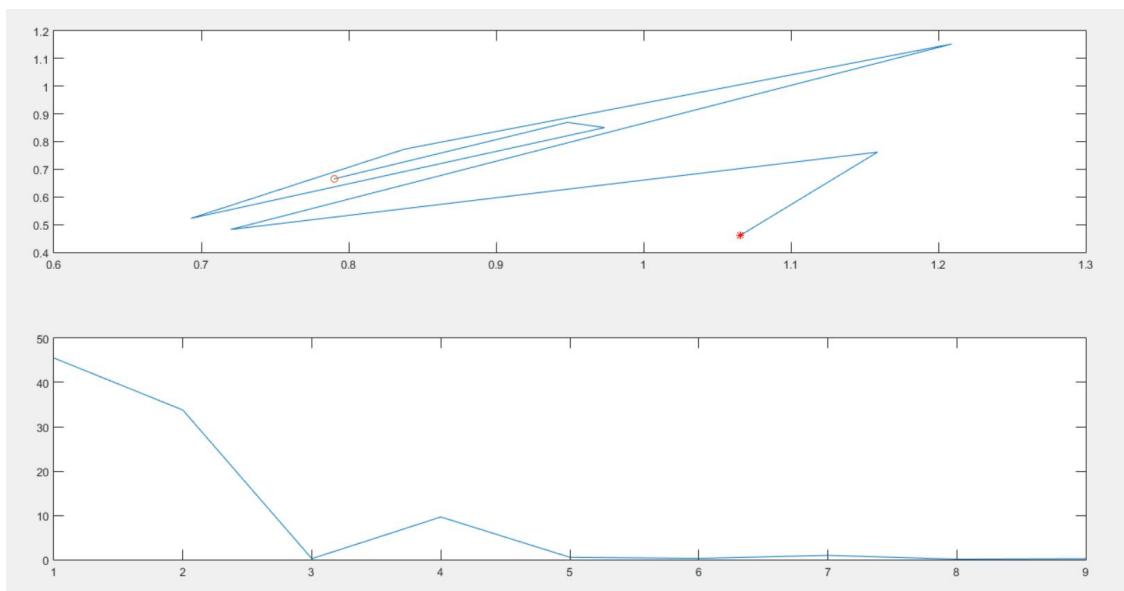
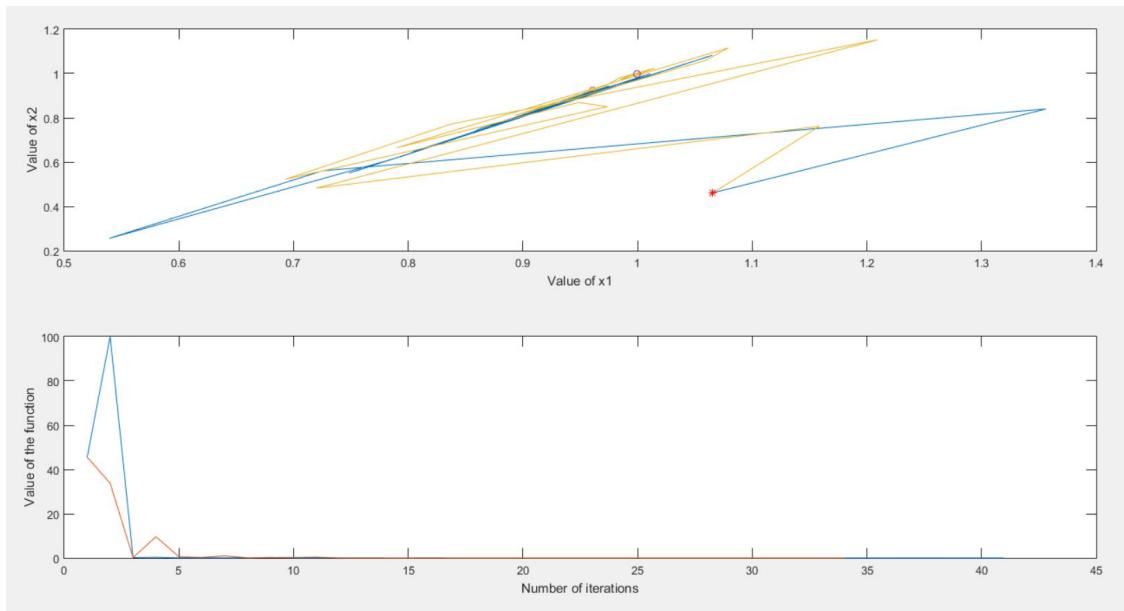


Figure 3.6: Particle 4

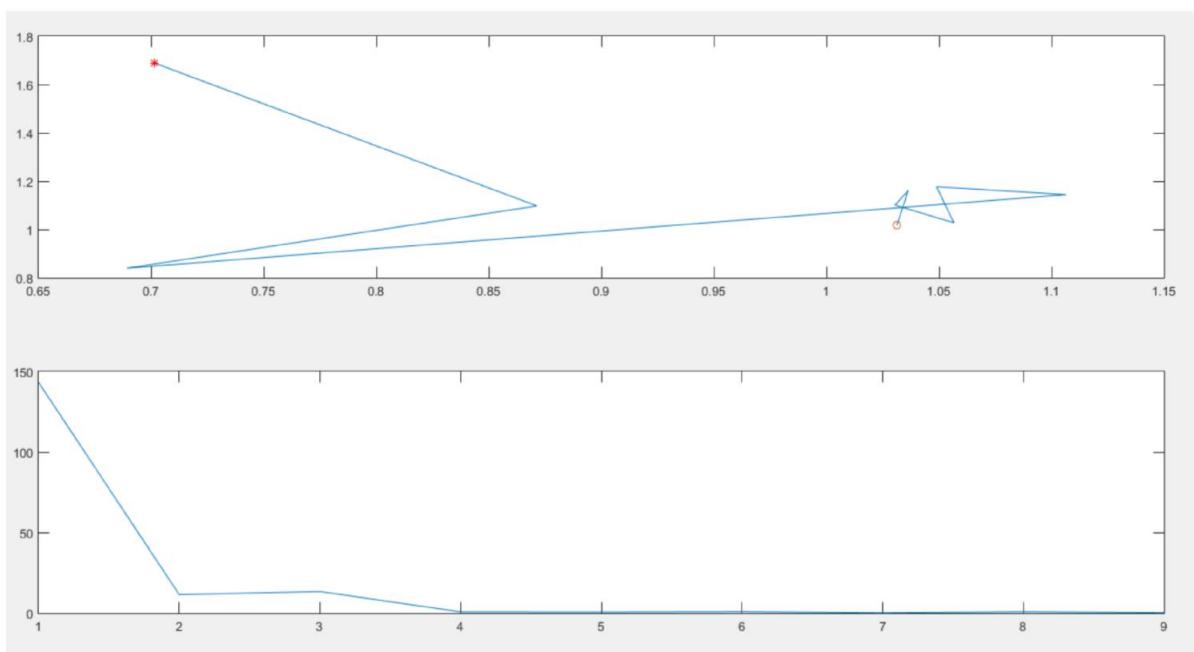
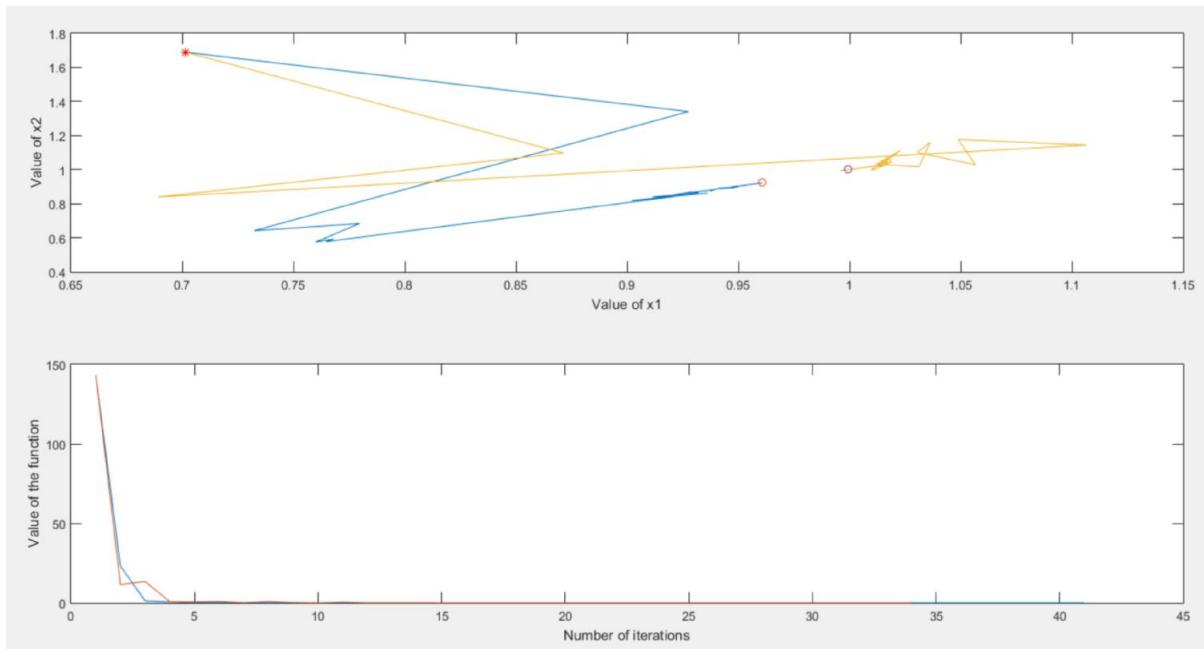


Figure 3.7: Particle 5

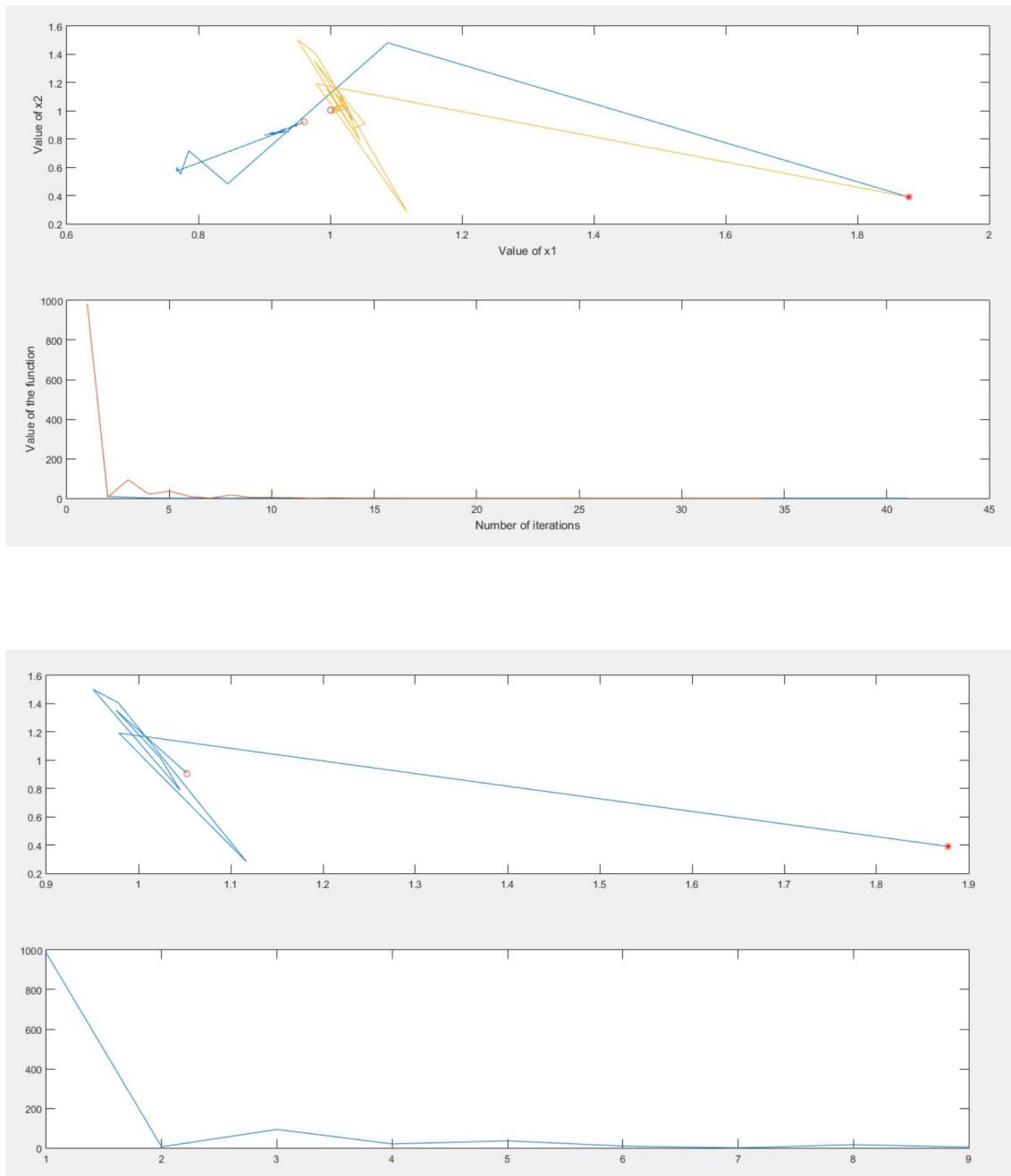


Figure 3.8: Particle 6

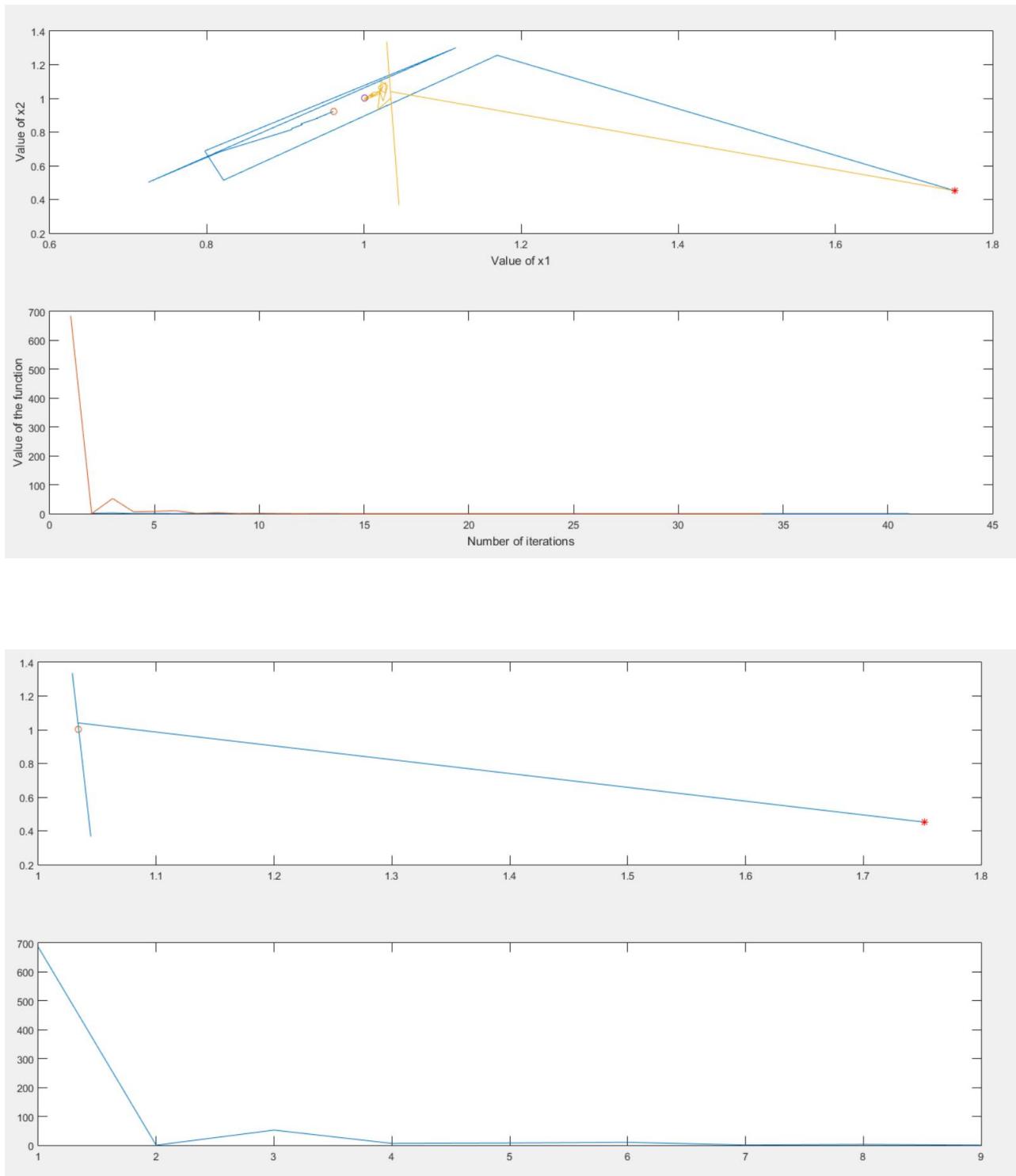


Figure 3.9: Particle 7

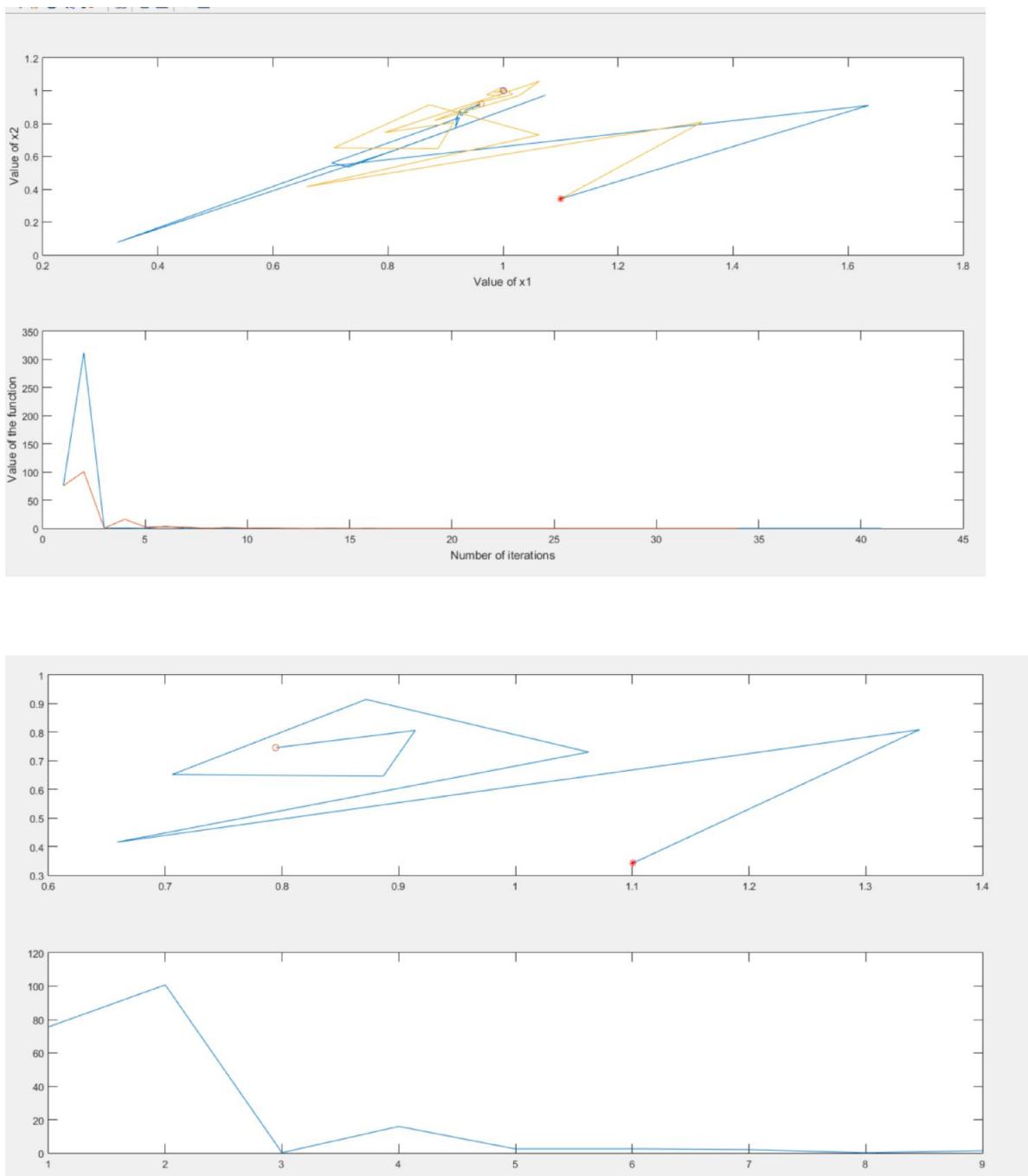


Figure 3.10: Particle 8

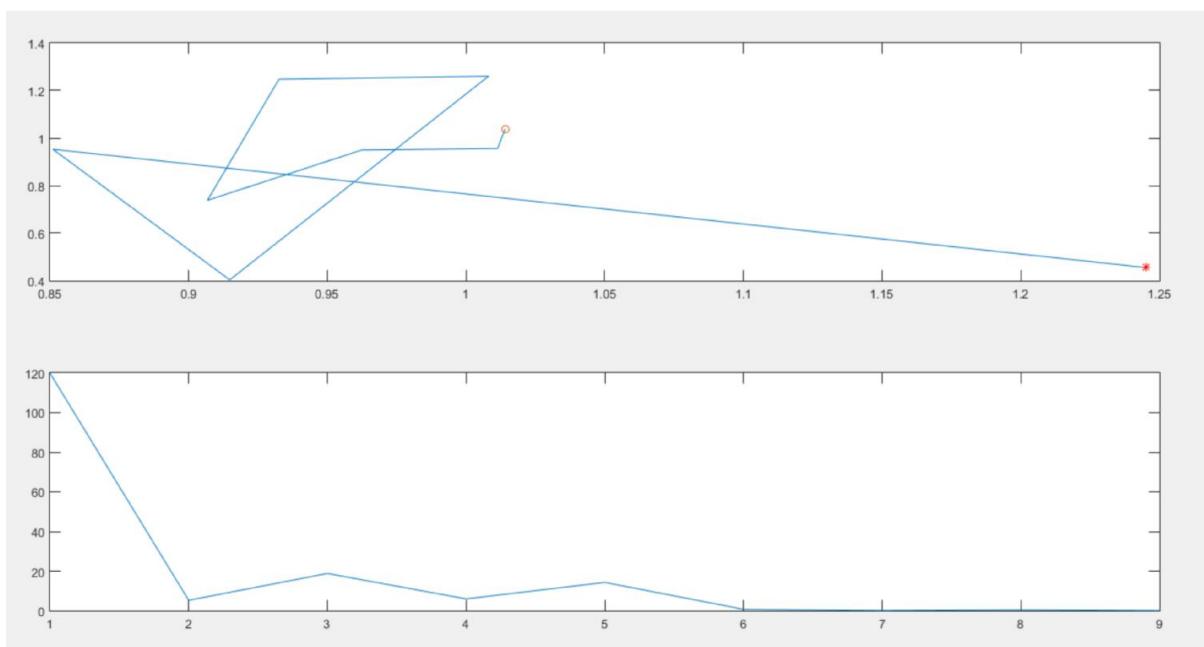
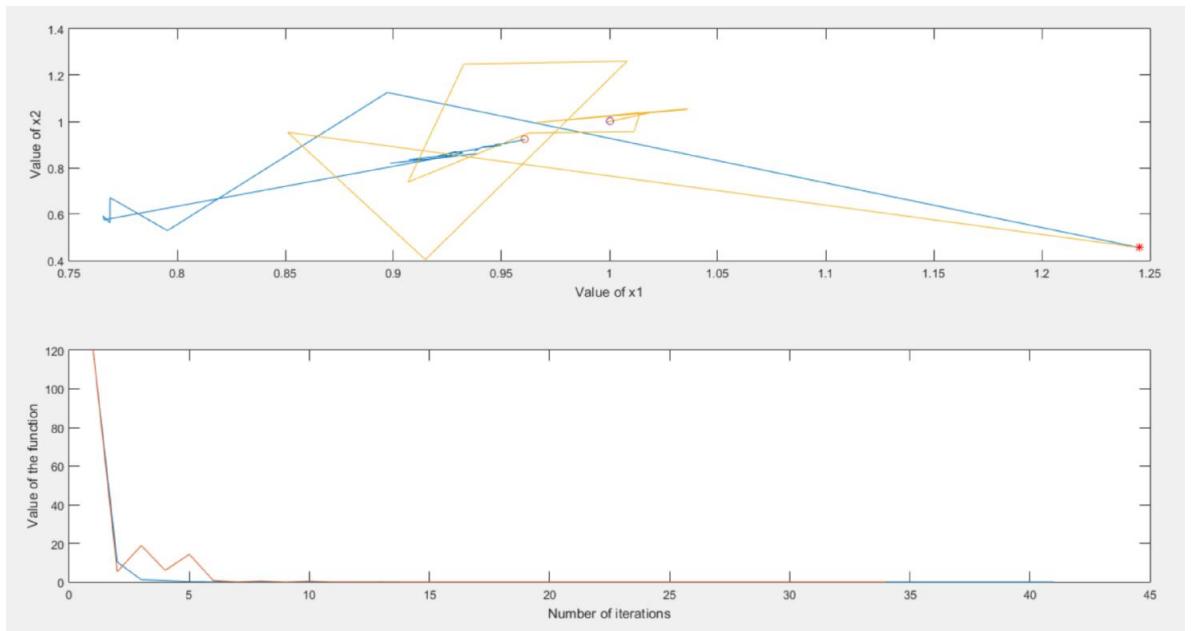


Figure 3.11: Particle 9

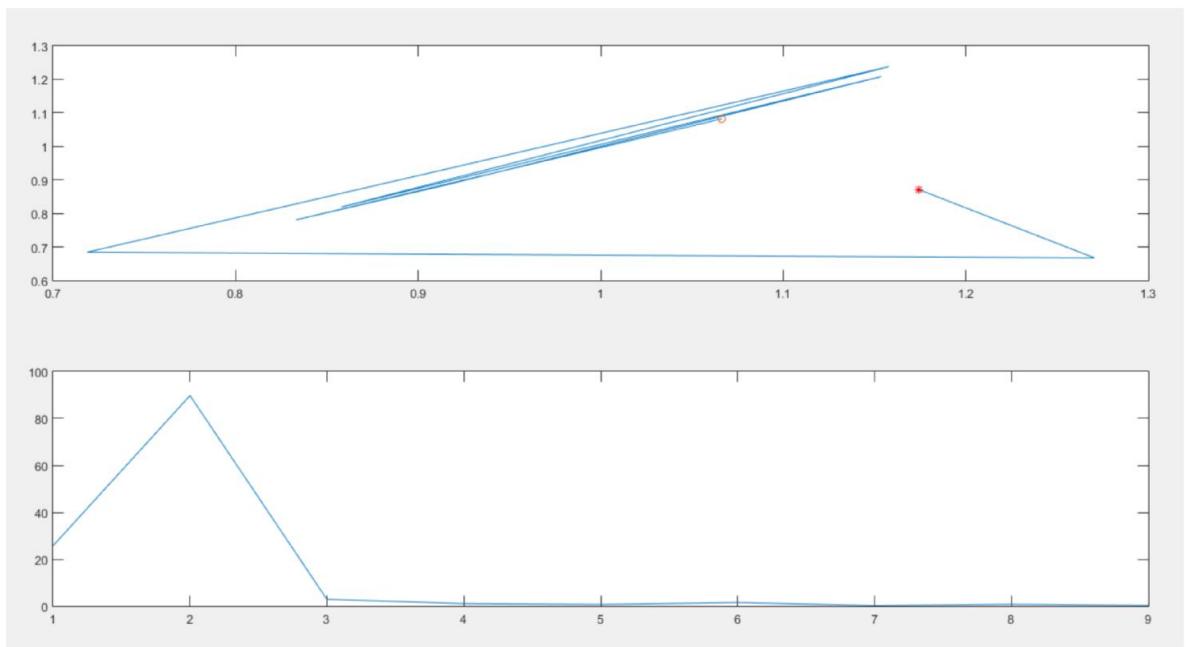
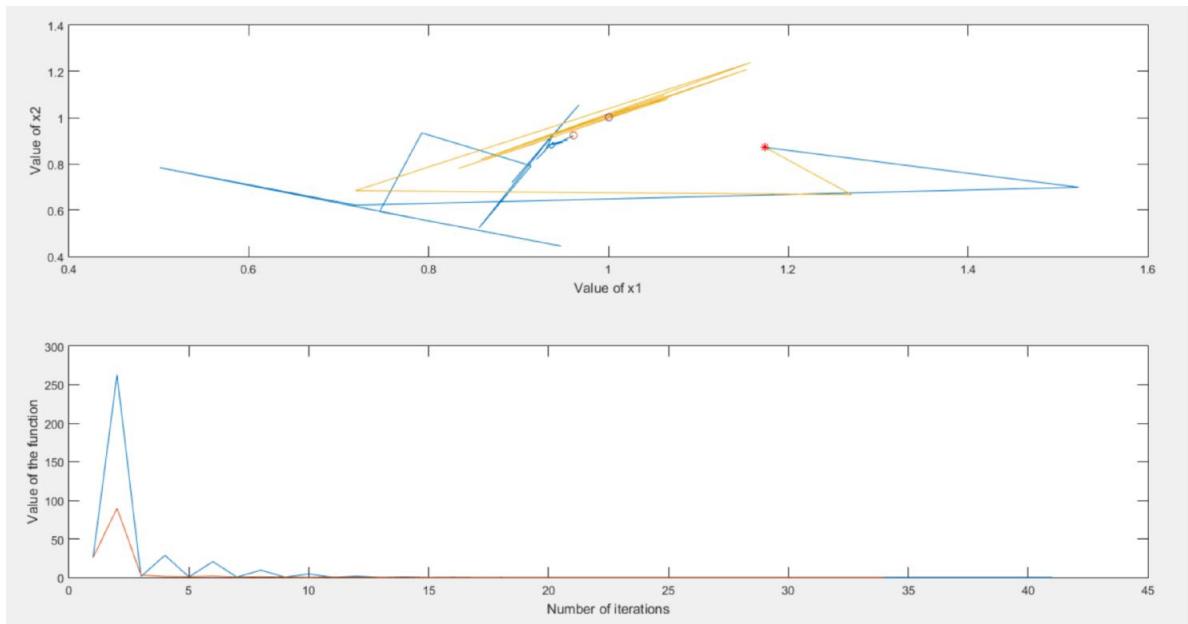


Figure 3.12: Particle 10

### 3.4 Conclusion

The star is the initial point for the particles and the circle denotes the last iteration at which the Rosenbrock function attains the minimum value i.e. near to zero. At this point the values of  $x_1$  and  $x_2$  are close to 1.

At the initial stages, the positions of the particles at each iteration are far apart from each other because initially the velocity of the particles is high. When the function starts approaching its optimum value, the velocity slows down and the points come closer to each other.

Varying the inertia weight  $\omega$ , greatly affects the trajectory of the particles. The best value was found to be at  $\omega=0.6$ . The values of  $x_1$  and  $x_2$  also converge at a value that is closer to 1 i.e. the actual solution.

As the value of the function approaches 0, the particles start vibrating or oscillating between roughly two nearby values till they reach the optimum point.

The particle 3 seems to be the best particle because the value of the function here along with the values of  $x_1$  and  $x_2$  converge to their ideal values quicker than the others.

Particle 2 is the worst particle as the values of the function as well as  $x_1$  and  $x_2$  are most far apart from each other in successive iterations and fluctuate a lot more as compared to the others.

# CHAPTER 4

## Analysis of Load Flow Studies using PSO: Field Application

---

### 4.1 Analysis for Load Flow Studies

In electrical engineering, the power flow study, also known as load flow study, may be used as a numerical tool in the analysis of the flow of electrical power in an interconnected load bus and generator bus system. A power flow study typically uses simplified notations and methods like a one-line diagram and per-unit system and focuses on numerous aspects of AC power parameters, like voltages, voltage angles, real power, and reactive power. It analyses the ability of systems in traditional steady state operation.

Load-flow studies are necessary for coming up with the long run enlargement of power systems along with determining the most effective operation requirements of existing systems. The principal data obtained from the power-flow study is the magnitude and phase angle of the voltage at every bus, and therefore the real and reactive power passing in every line.

Commercial power systems are typically too complicated to permit for manual resolution of the power flow study. For this purpose, between 1929 and the early sixties, special network analysers were engineered to produce laboratory scale physical models of power systems. Analogue ways with numerical solutions were replaced by large scale digital computers owing to a boom in technology and science..

In addition to a power flow calculative effort, some other connected functions like short-circuit fault analysis, stability studies (transient and steady state), unit commitment and economic load dispatch are also effec-

tively performed by computer programs. Specifically, some coded algorithms use applied math to search out the best power flow, the conditions that provide an all-time low price per kilowatt hour delivered to the arrangement.

A load flow study is particularly valuable for a system with more than one load centres like a complex refinery etc. Analysis of the system's ability to adequately offer and supply the connected load is done using power flow study. The whole system losses, added together as individual line losses, are also tabulated in a proper form. Working with a load flow study provides insights and proposals on the system operation and improvement of management settings to get the most capability whereas minimizing the operational prices. The outcomes of such analysis are measured in terms of active power generated and injected, reactive power generated and injected, their magnitudes, and phases. Moreover, power-flow results and solutions obtained are extremely important for optimal operations of teams of generating units.

In term of its approach towards irregularities, load flow study is divided into deterministic load flow and load flow handling uncertainties. The uncertainties that arise from each power generation cycle and unorganized load behavioural changes are not taken into consideration in deterministic load flow studies. To take the uncertainties into thought, there are many methods employed like possibility, data gap call theory, probabilistic, interval analysis, and strong improvement.

Load flow problem is iterative, utilizing the Gauss-Seidel methods or the Newton-Raphson techniques. The Newton-Raphson method, or Newton method, is an incredible system for unravelling conditions numerically. Like most of the infinitesimal calculus, it's supported the easy plan of linear approximation. But, in recent times, there has been abundant interest within the application of random search ways, like Genetic Algorithms or particle swarm optimization technique to resolution power grid issues. This problem typically targets to get the system buses voltages – module and angle – so as to see later the ability changes within the generation buses and therefore the power flow within the system lines. The system operating within the steady-state, i.e., its parameters not varying with the time variation is provided by the load flow study. The power flow calculation

is additionally important pertaining to the setting of an optimal point of operation, concerning economy and quality. When the system has known steady state, it's attainable to approximate the quantity of power required to be generated necessarily to produce the ability demand and the power losses. within the system lines, furthermore the voltage levels should be unbroken inside the boundaries and full operations, besides the operations within the stability limit should be avoided. Load flow analysis depend on a powerful framework and its voltage investigation performed nodally.

The **Static Load Flow Equations (SLFE)** in its general form is characterised by:

$$P_i - jQ_i = y_{i1}V_1V_i * -y_{i2}V_2V_1 * -... - y_{in}V_nV_i* = 0 \quad (4.1)$$

where:  $i = 1, \dots, n$ , bus number;

$P_i$  = active power generated or injected in the bus  $i$ ;

$Q_i$  = reactive power generated or injected in the bus  $i$ ;

$|V_i|$  = voltage module of the bus  $i$ ;

$\delta_i$  = voltage angle of the bus  $i$ ;

$V_i = |V_i|e^{j\delta_i}$

;

$i$  = voltage angle of the bus  $i$ ;

The subsequent explanation explains how the nodal admittance matrix is obtained: if  $i = k$ ,  $y_{ik}$  is that the total of the admittances that startup of the bus  $i$ ; and if  $ik$ ,  $y_{ik}$  is that the admittance between the buses  $i$  and  $k$ , multiplied by -1. The power framework transports are characterized in sorts, as indicated by the factors known from the earlier and to the factors that will be gotten through the SLFE.

- Type 1 Bus or PQ Bus:  $P_i$   $Q_i$  are indicated and  $-Vi$  and  $\delta_i$  are gotten through the SLFE;
- Type 2 Bus or PV Bus:  $P_i$   $-Vi$  are determined and  $Q_i$  and  $\delta_i$  are acquired through the SLFE;
- Type 3 Bus or V Bus ("Slack Bus"):  $|Vi|$  and  $\delta_i$  are determined and  $P_i$   $Q_i$  are acquired through the SLFE.

Equation plays out indirect and complicated conditions framework, and its answer is gotten by using estimations utilizing mathematical computational techniques. The Gauss, Gauss-Seidel and Newton Raphson strategies are regularly connected to tackle these frameworks. The most utilized technique is Newton Raphson because of its more noteworthy assurance and fast achievement of union. The strategies comprise in the appropriation of starting evaluated qualities to the transport voltages, module 1,0 [pu] and point 0 [rad], for example, and in the use of the SLFE in progressive cycles, hunting down finer estimations for the voltages. The stopping paradigm differs as indicated by the required exactness.

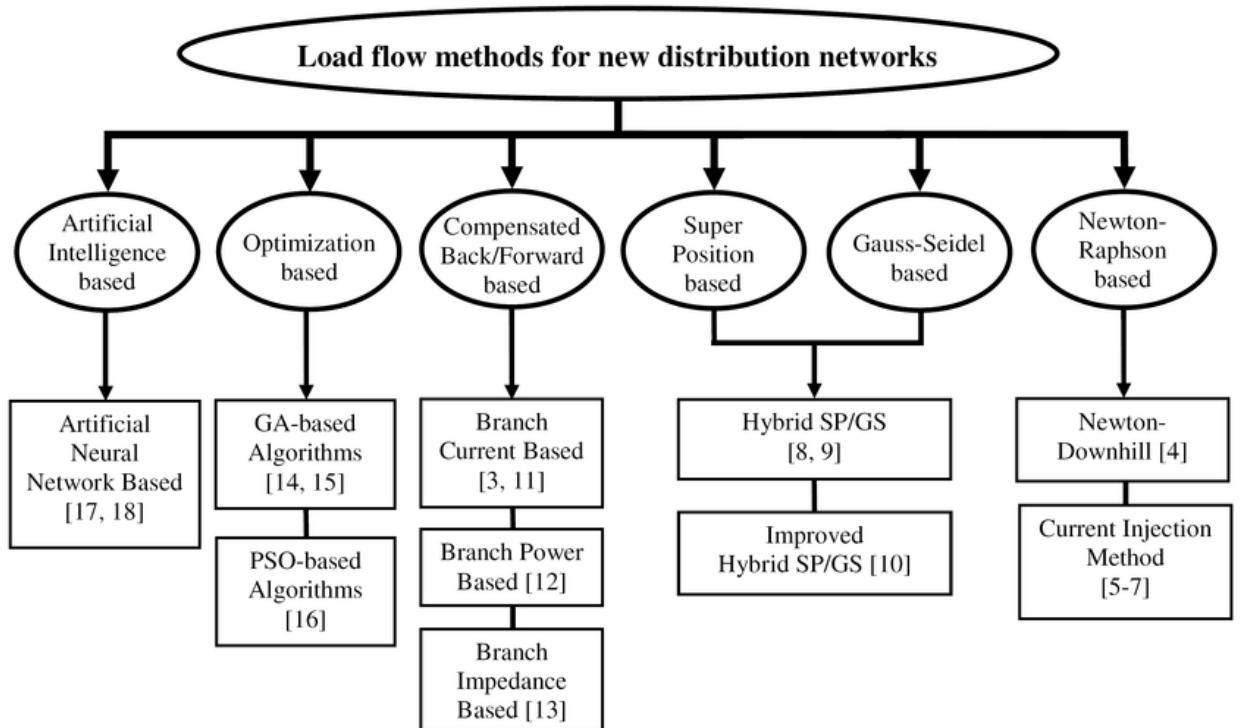


Figure 4.1: Loadflow methods

The conventional load flow methods used for power systems are as follows:-

1. Newton-Raphson (NR) method
2. Gauss-Seidel method with impedance matrix (ZGS)
3. Gauss-Seidel method with admittance matrix (YGS)
4. Fast Decoupled Newton-Raphson (FDNR)
5. Decoupled Newton-Raphson (DNR)

The extremely necessary load flow techniques, that can be applied to new distribution arrangements, are classified into 6 distinct areas: NR based strategies, Gauss-Seidel based techniques, superposition based strategies, remunerated in reverse/forward range techniques, enhancement based strategies and computerized reasoning based techniques. In our venture we expect to tackle the above issue utilizing an Evolutionary Algorithm i.e. **Particle Swarm Optimization**

## 4.2 Implementation Details

The PSO algorithm to a 5 bus system containing 3 load buses, 1 generator bus and 1 slack bus. The injection and generation of both active and reactive powers to and from each buses been calculated along with the cost of generation. The mismatch in the calculated and the specified values of the active and reactive powers has been taken as the objective function that is minimised using the Particle swarm optimization. The line losses in each line have also been calculated. The step by step flowchart along with the Output is given below:

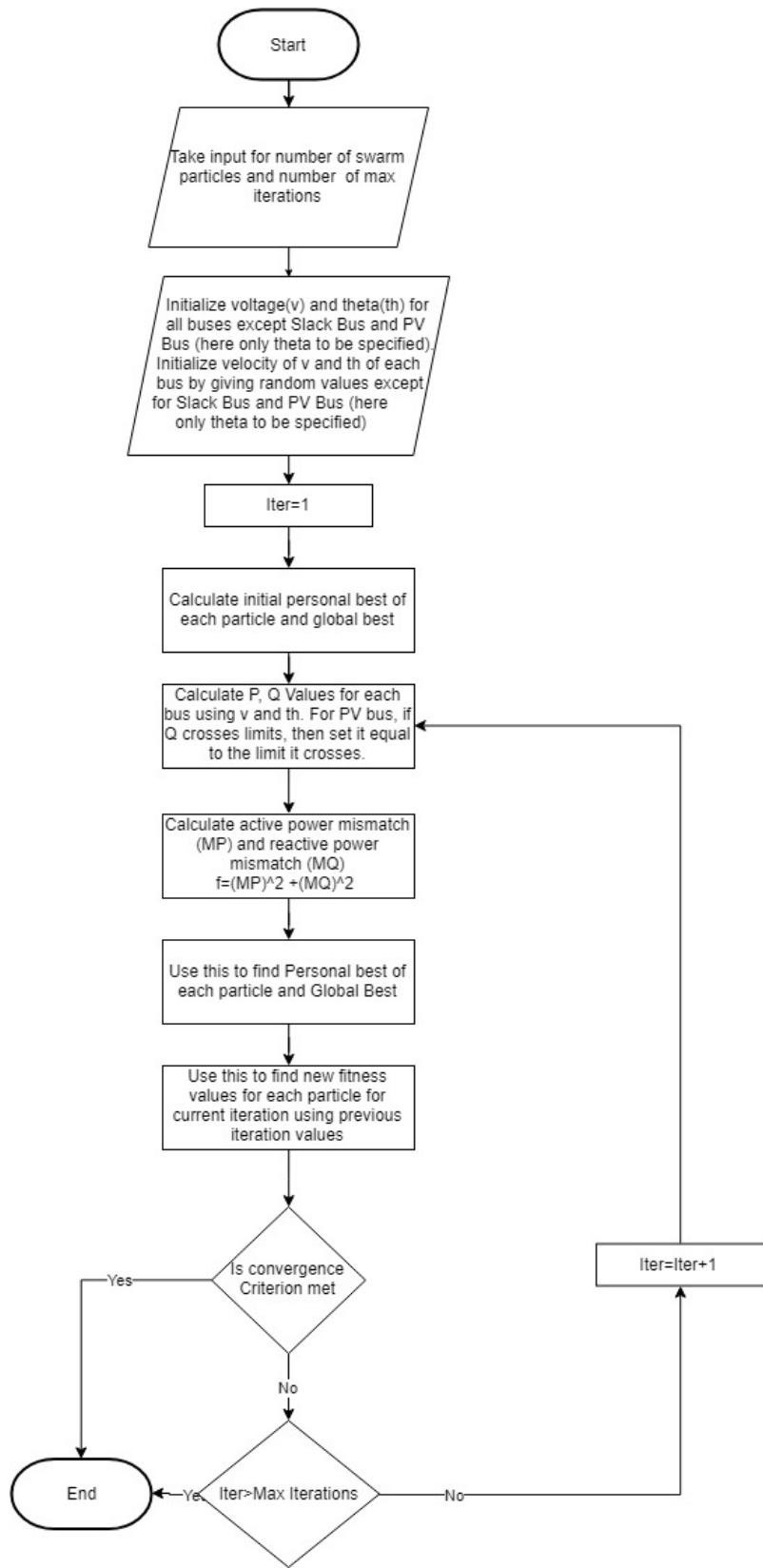


Figure 4.2: Loadflow methods

### 4.2.1 Output

PSO Loadflow Analysis									
Bus	V	Angle	Injection		Generation		Load		
No	pu	Degree	MW	MVar	MW	Mvar	MW	MVar	
1	1.0200	0.0000	65.150	32.916	65.150	80.599	0.000	0.000	
2	0.9548	-3.9413	-60.000	-30.000	0.000	0.000	60.000	30.000	
3	1.0400	2.0008	100.000	47.684	100.000	0.000	0.000	0.000	
4	0.9235	-8.0078	-40.000	-10.000	0.000	0.000	40.000	10.000	
5	0.9931	-2.0726	-60.000	-20.000	0.000	0.000	60.000	20.000	
Total			5.150	20.599	165.150	80.599	160.000	60.000	

Table 4.1: PSO Loadflow Analysis

Line Flow and Losses									
From	To	P	Q	From	To	P	Q	Line Loss	
Bus	Bus	MW	MVar	Bus	Bus	MW	MVar	MW	MVar
1	2	19.800	12.264	2	1	-19.279	-10.178	0.521	2.086
1	4	24.805	11.743	4	1	-23.719	-7.399	1.086	4.344
1	5	20.545	8.909	5	1	-20.304	-7.945	0.241	0.964
2	3	-57.321	-23.698	3	2	59.431	32.139	2.110	8.441
2	4	16.600	3.876	4	2	-16.281	-2.601	0.319	1.275
3	5	40.569	15.545	5	3	-39.696	-12.055	0.873	3.490
Total Loss								5.150	20.599
Total Loss = 5.150									

Table 4.2: Line Flow and Losses

## Description for Output

- Total number of iterations=258
- In the injection column of PSO load flow analysis, the positive quantities indicate that power flows out of the bus and negative quantities indicate that power flows into the bus.
- The sum of all injections gives Total Losses which is equal to 5.150 MW. This can also be seen from Line Loss (MW) of Line Flow and Losses Table.
- From output, Total generation is 165.150 MW and total load is 160 MW. This again gives losses=5.150 MW.
- Below graphs depict the value of the different parameters like the objective function value, value of theta and voltage for a particular particle for 100 iterations

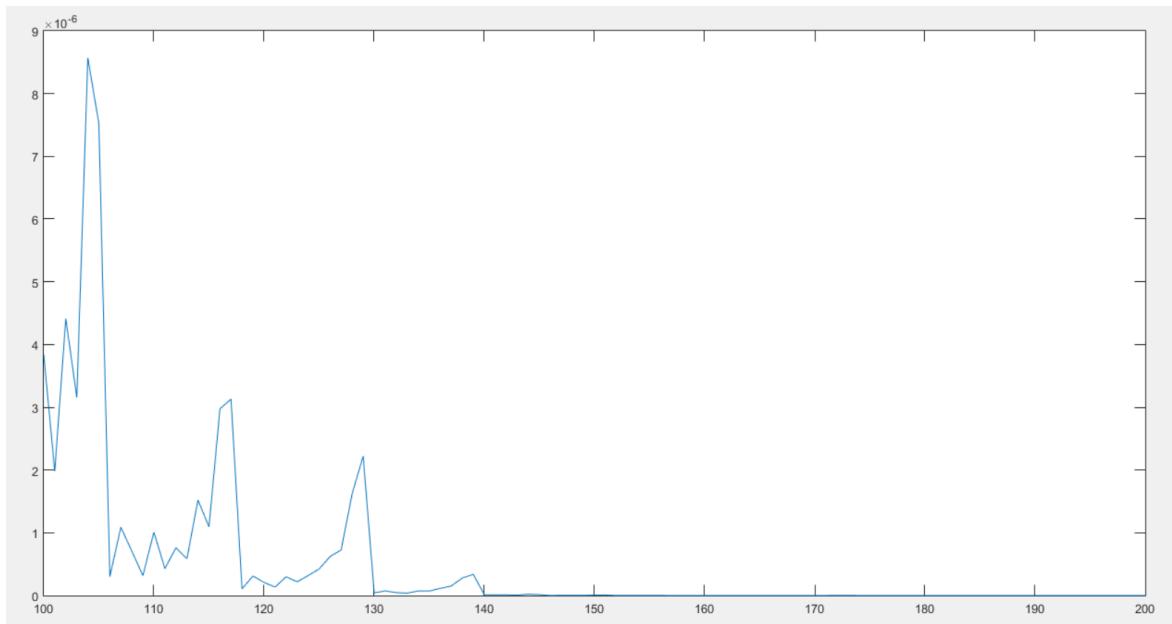


Figure 4.3: OBJECTIVE FUNCTION V/S ITERATIONS

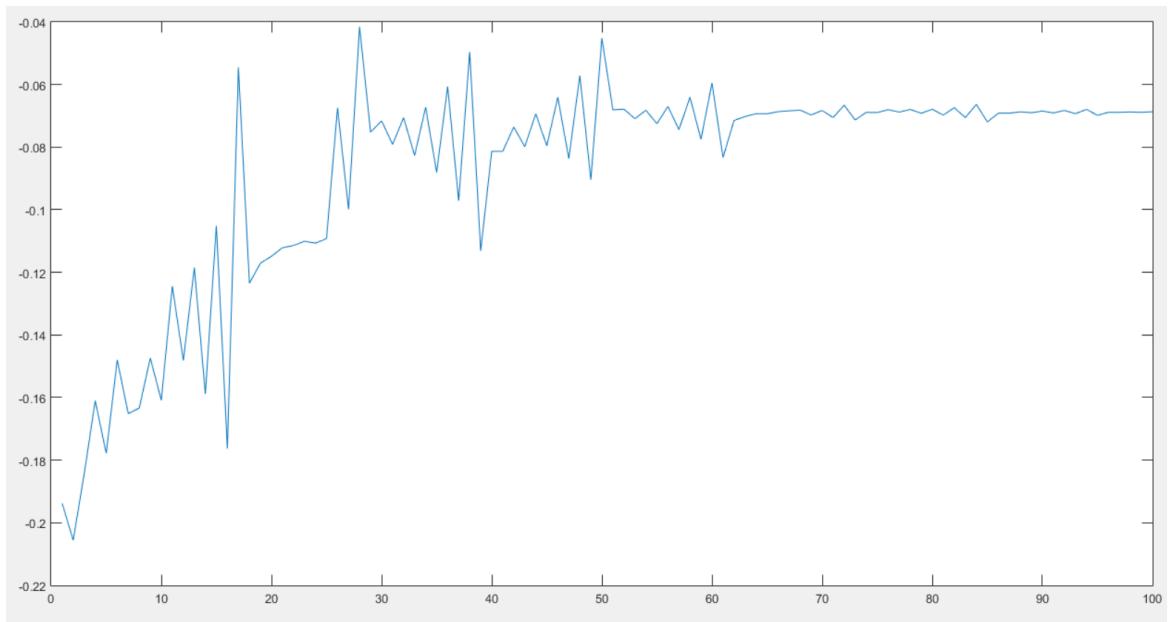


Figure 4.4: THETA BUS 2 V/S ITERATIONS

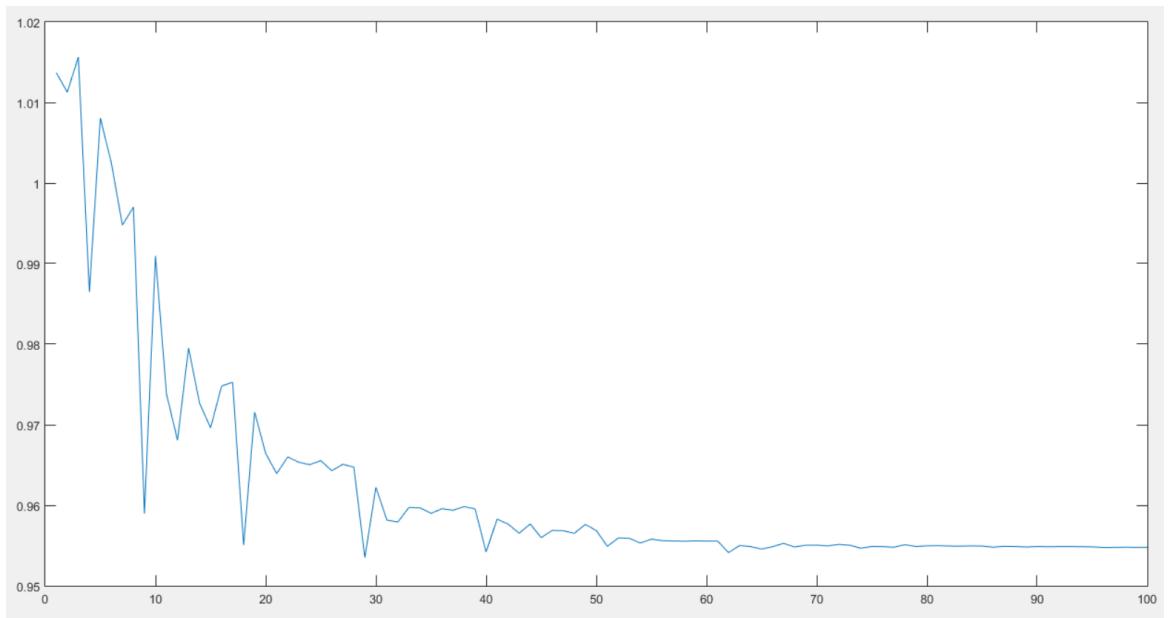


Figure 4.5: VOLTAGE BUS 2 V/S ITERATIONS

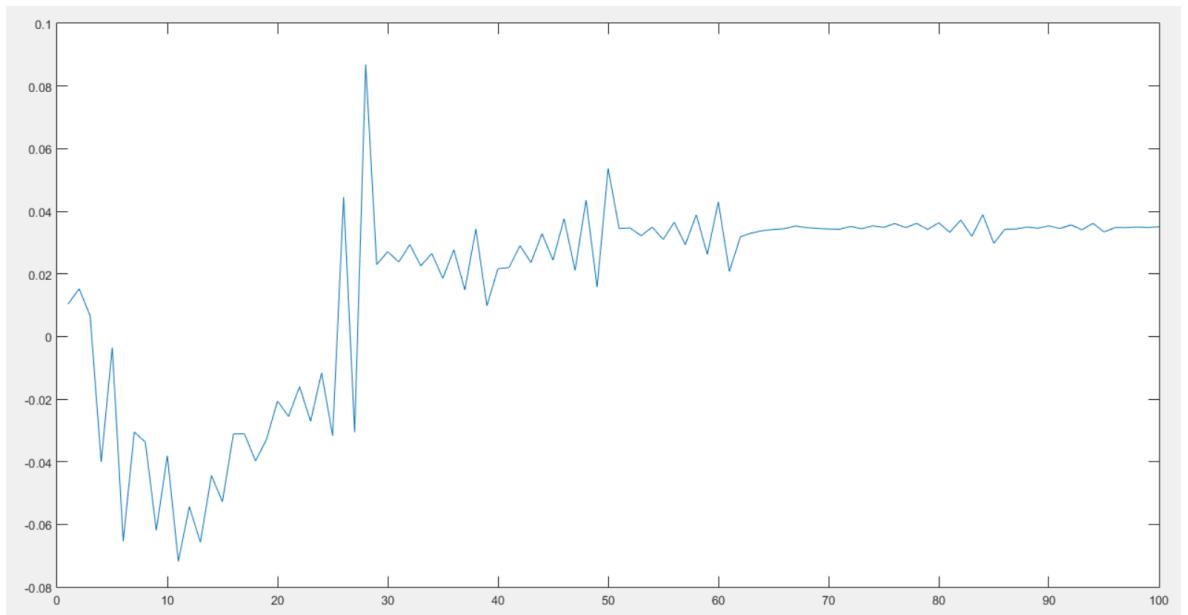


Figure 4.6: THETA BUS 3 V/S ITERATIONS

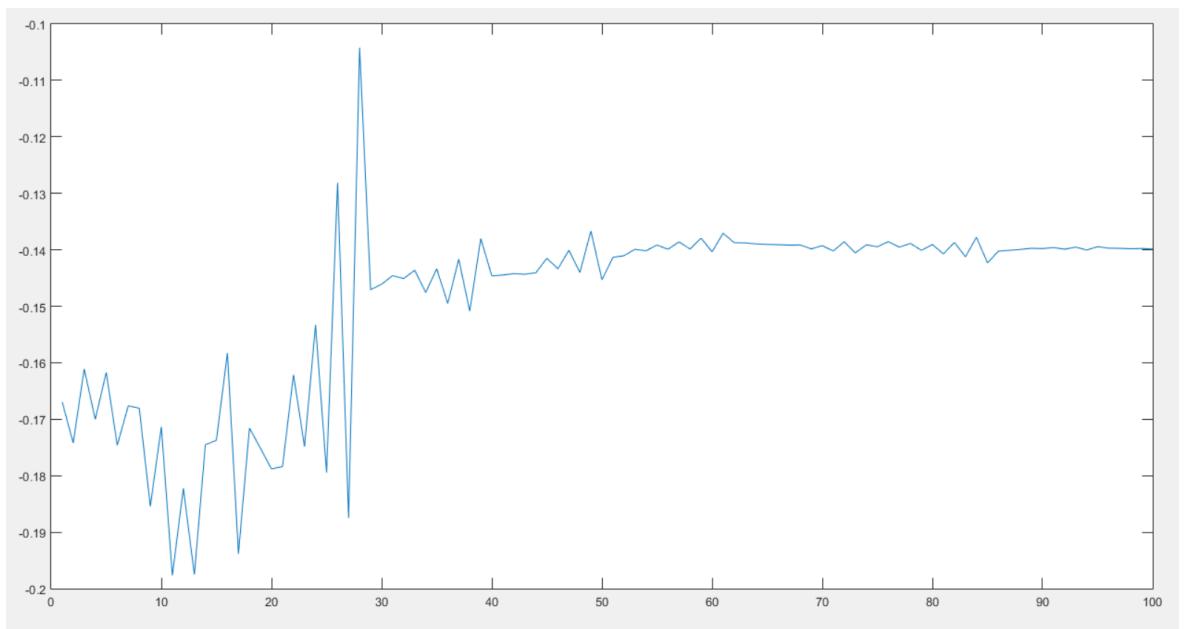


Figure 4.7: THETA BUS 4 V/S ITERATIONS

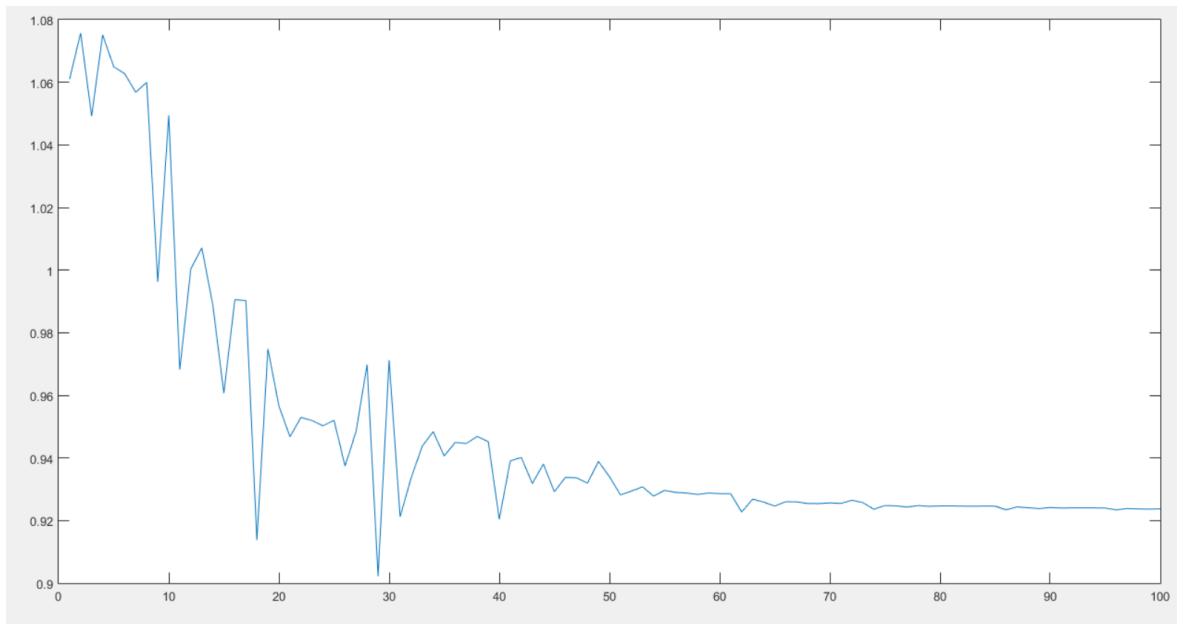


Figure 4.8: VOLTAGE BUS 4 V/S ITERATIONS

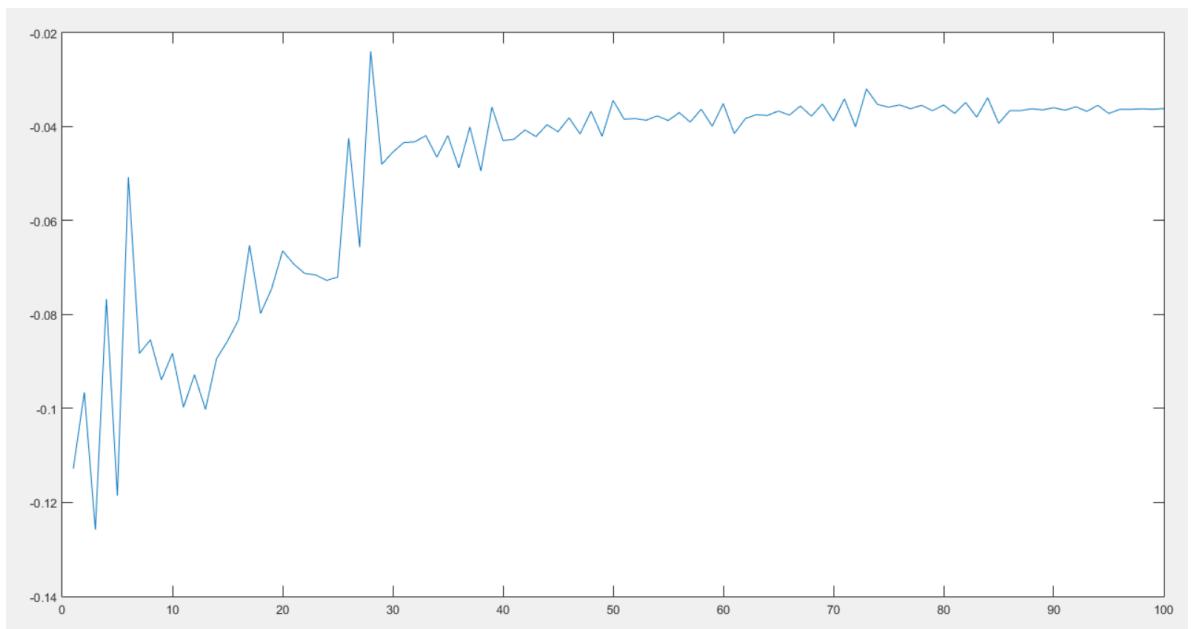


Figure 4.9: THETA BUS 5 V/S ITERATIONS

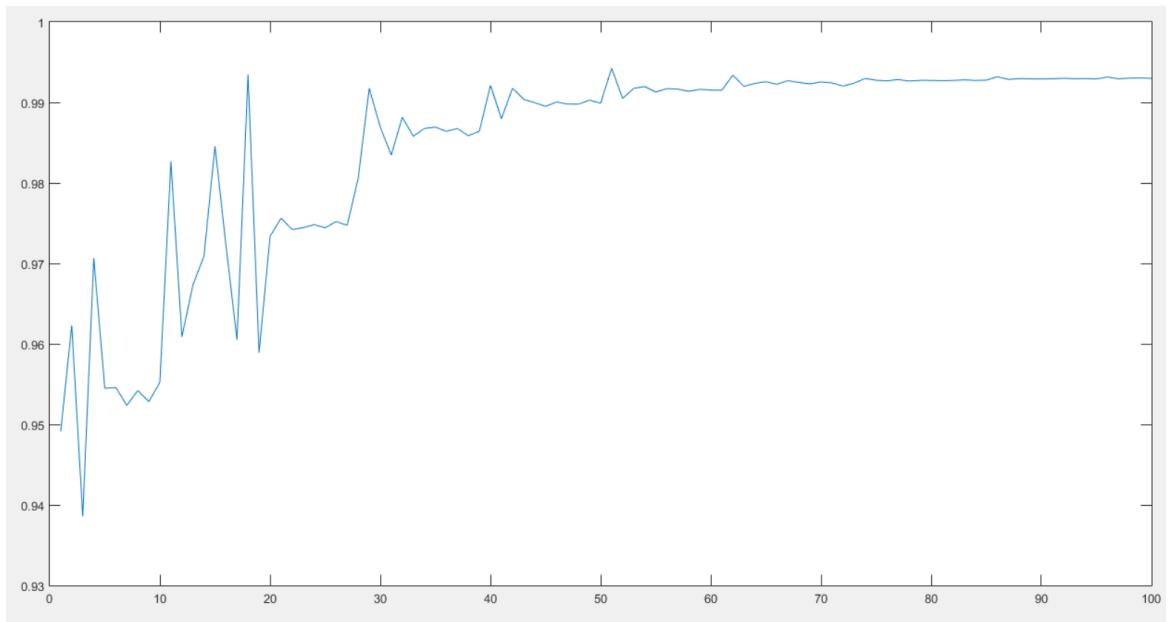


Figure 4.10: VOLTAGE BUS 5 V/S ITERATIONS

# CHAPTER 5

## Improvement in PSO applied to Load Flow Studies

---

### 5.1 Positional Weightage PSO in Load Flow

From the previous method, it can be seen that before the particle swarm approached the true solutions, each individual particle made a high number of vibrations, i.e. the particle's value oscillated about the true solutions before the particle finally converged there.

In order to make the PSO program more efficient, the number of iterations have to be reduced.

Thus, in order to achieve this, we aim to reduce the vibrations. These can be reduced if all the particles were repositioned after some time, so that each particle was closer to true solution. This reduces the vibrations of each individual particle as well as the effect of one particle on others that caused others to stray away from true solution.

The particles have higher vibrations or higher amplitude of variations in the initial set of iterations ie. from 1-40. If it is desired to reposition the particles, it is best to do it within this initial set of iterations because if we are able to reduce the larger variations at the beginning itself, we will be able to reach the result faster.

The algorithm followed is:

1. Let program run normally till a fixed number of iterations. (Say 15)
2. For each particle, take into account its personal best and global best till the present iteration. Assign weight to each position depending upon the value and kind of solution we need (Maxima/minima). Higher the weight, better will be the position.
3. A factor called global weightage factor ( $s_1$ ) is also present along with function value at global best in order to further control and optimize the weight assigned to global best position.
4. Finally, take the weighted mean and continue the program to run as normal.

This approach not only reduces the vibrations, but also prevents a possible solution part of the function, that in normal case might be left out or be reached after longer time, to be taken into account.

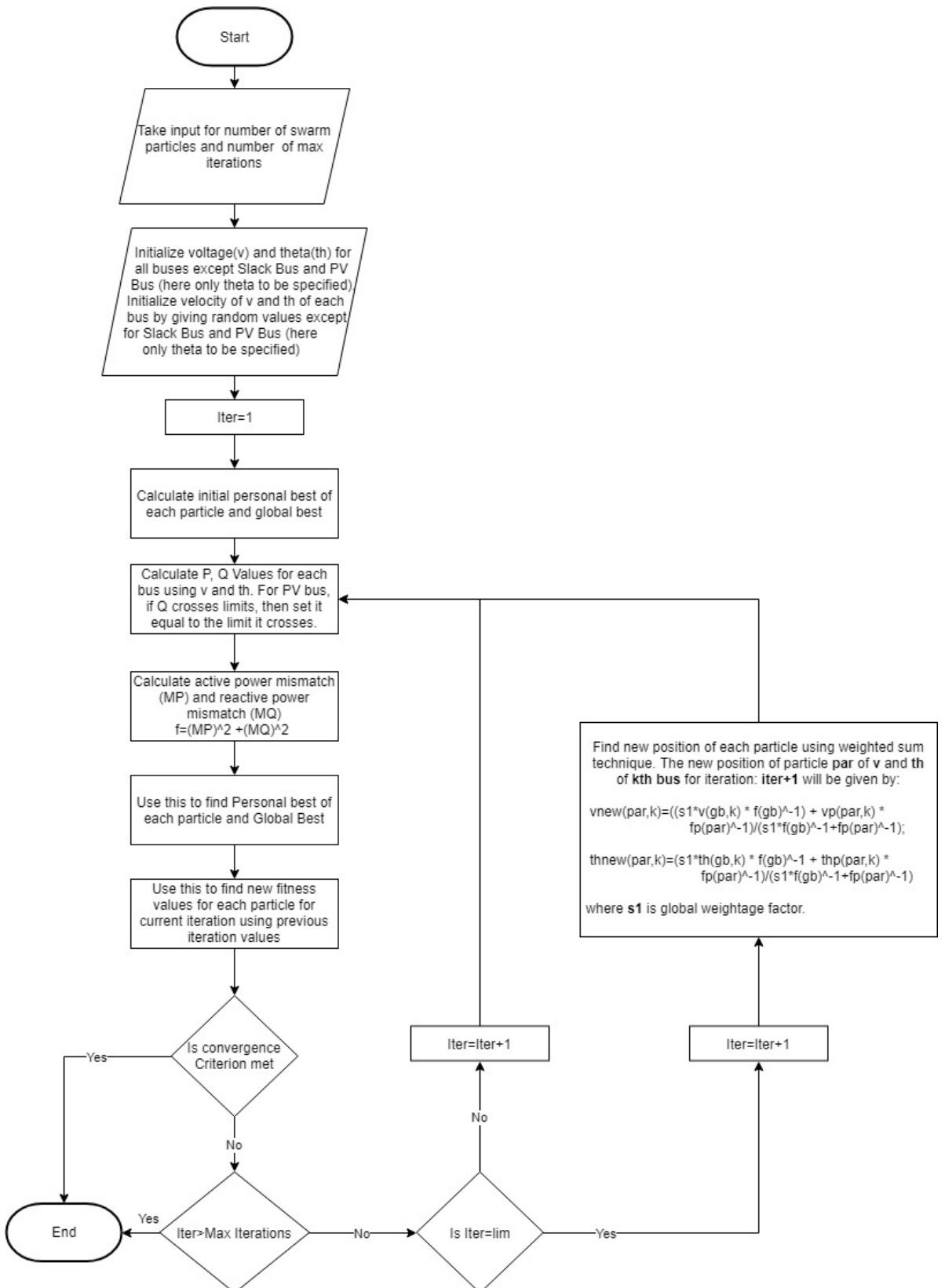


Figure 5.1: Flowchart for the process

## 5.2 Output

$$LIM = 15$$

$$S_1 = 0.493$$

PSO Loadflow Analysis									
Bus	V	Angle	Injection		Generation		Load		
No	pu	Degree	MW	MVar	MW	Mvar	MW	MVar	
1	1.0200	0.0000	65.151	32.916	65.150	80.599	0.000	0.000	
2	0.9548	-3.9414	-60.000	-30.000	0.000	0.000	60.000	30.000	
3	1.0400	2.0007	99.999	47.684	100.000	0.000	0.000	0.000	
4	0.9235	-8.0078	-40.000	-10.000	0.000	0.000	40.000	10.000	
5	0.9931	-2.0726	-60.000	-20.000	0.000	0.000	60.000	20.000	
Total			5.150	20.599	165.150	80.599	160.000	60.000	

Table 5.1: PSO Loadflow Analysis using Improved PSO

Line FLow and Losses									
From	To	P	Q	From	To	P	Q	Line Loss	
Bus	Bus	MW	MVar	Bus	Bus	MW	MVar	MW	MVar
1	2	19.801	12.264	2	1	-19.279	-10.178	0.521	2.086
1	4	24.805	11.743	4	1	-23.719	-7.399	1.086	4.344
1	5	20.545	8.909	5	1	-20.304	-7.945	0.241	0.964
2	3	-57.321	-23.698	3	2	59.431	32.139	2.110	8.441
2	4	16.599	3.876	4	2	-16.281	-2.601	0.319	1.275
3	5	40.569	15.545	5	3	-39.696	-12.055	0.873	3.490
Total Loss								5.150	20.599
Total Loss = 5.150									

Table 5.2: Line Flow and Losses

## GRAPHICAL OUTPUTS IN THE ANALYSIS OF LOAD FLOW STUDY USING IMPROVED PSO SHOWING VARIATIONS IN PARTICLES OF VARIOUS PARAMETERS WITH ITERATIONS

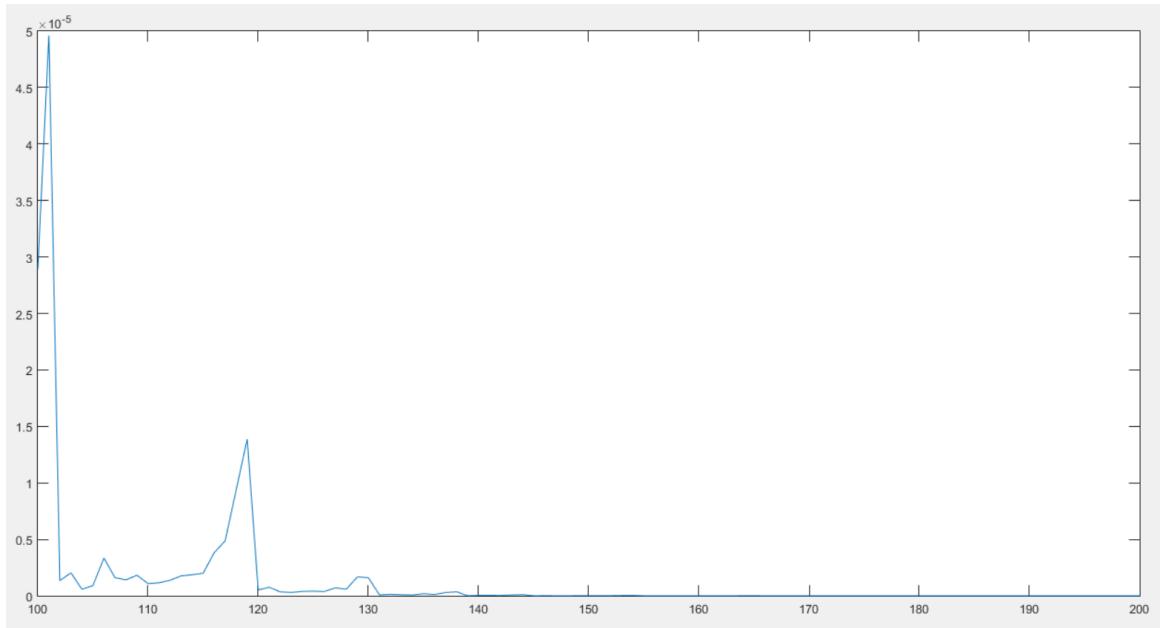


Figure 5.2: GRAPH FUNCTION IMPROVED PSO V/S ITERATIONS

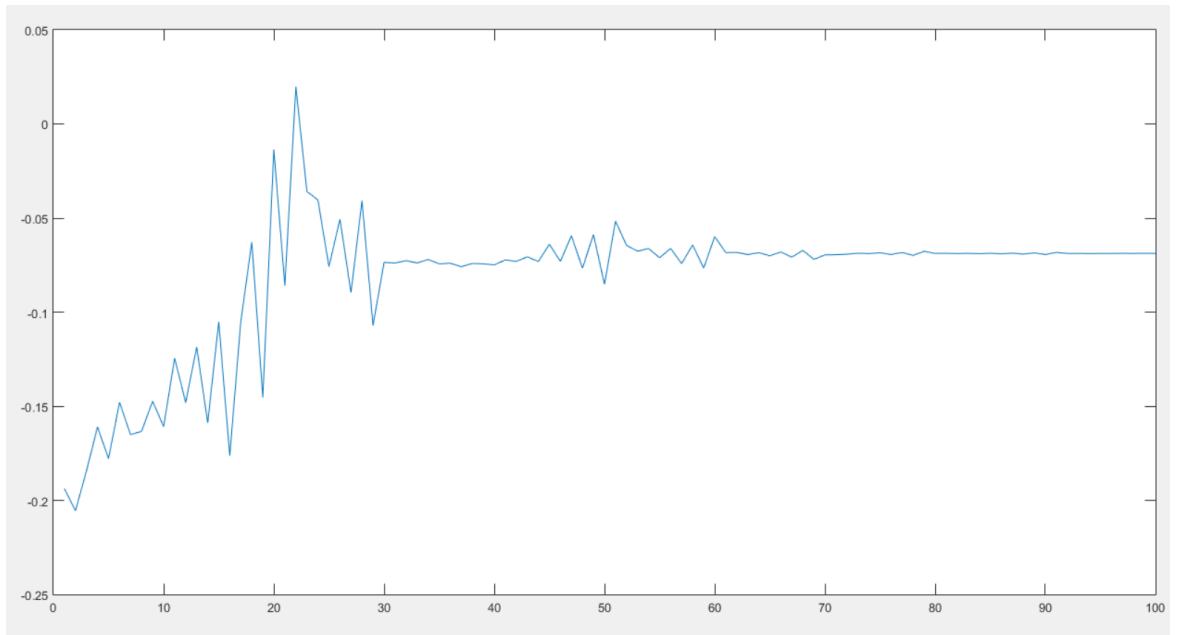


Figure 5.3: THETA BUS 2 V/S ITERATIONS

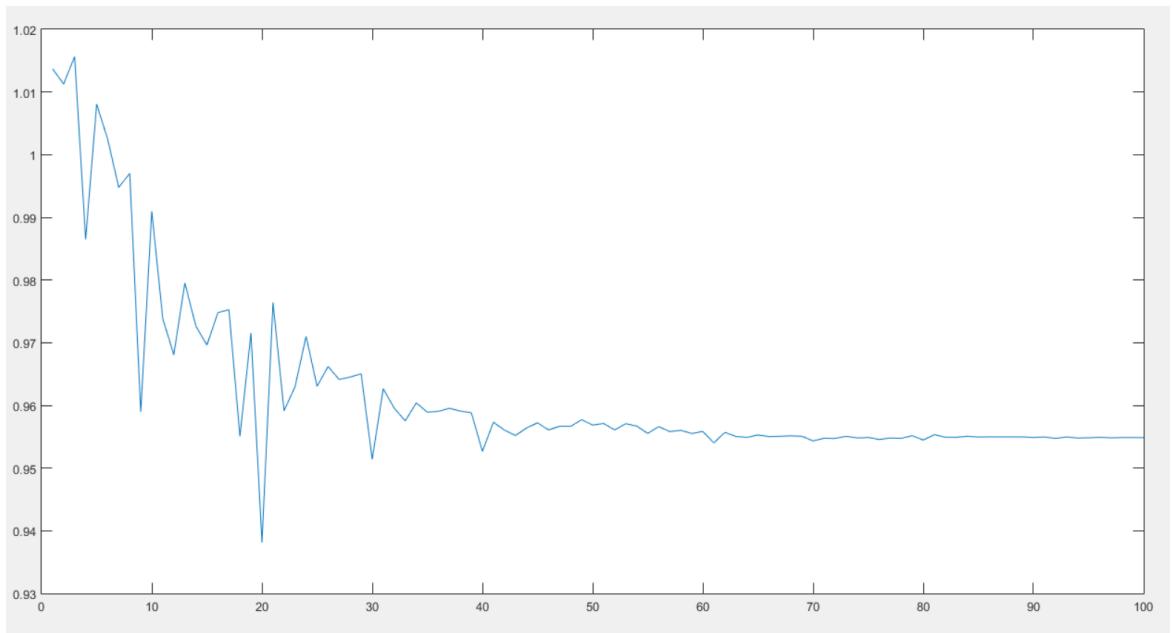


Figure 5.4: VOLTAGE BUS 2 V/S ITERATIONS

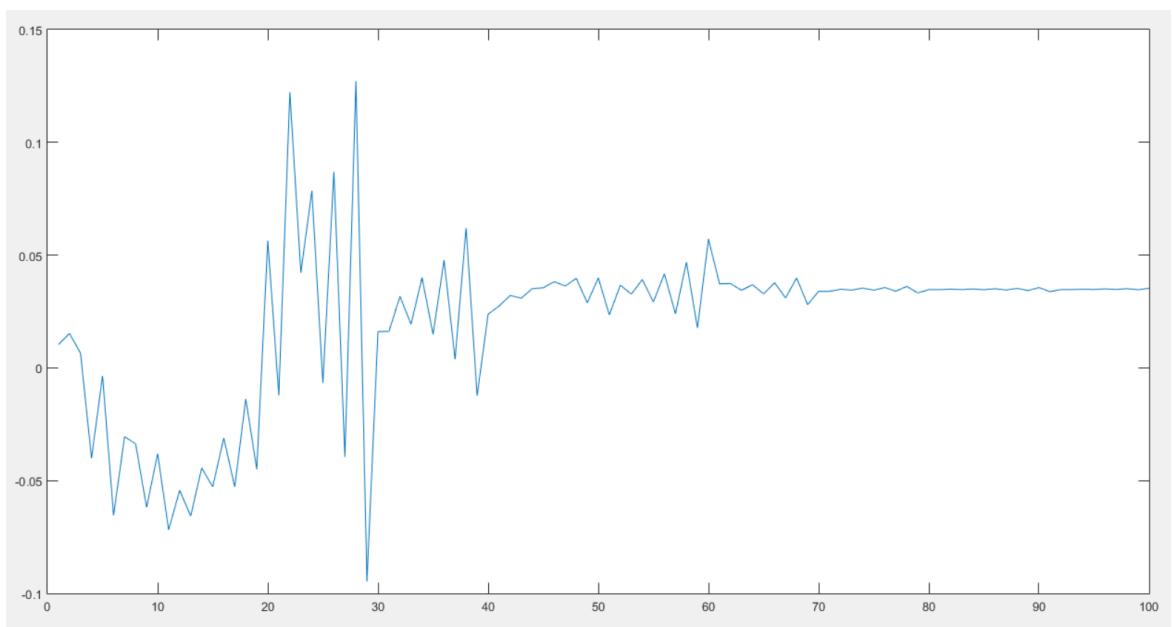


Figure 5.5: THETA BUS 3 V/S ITERATIONS

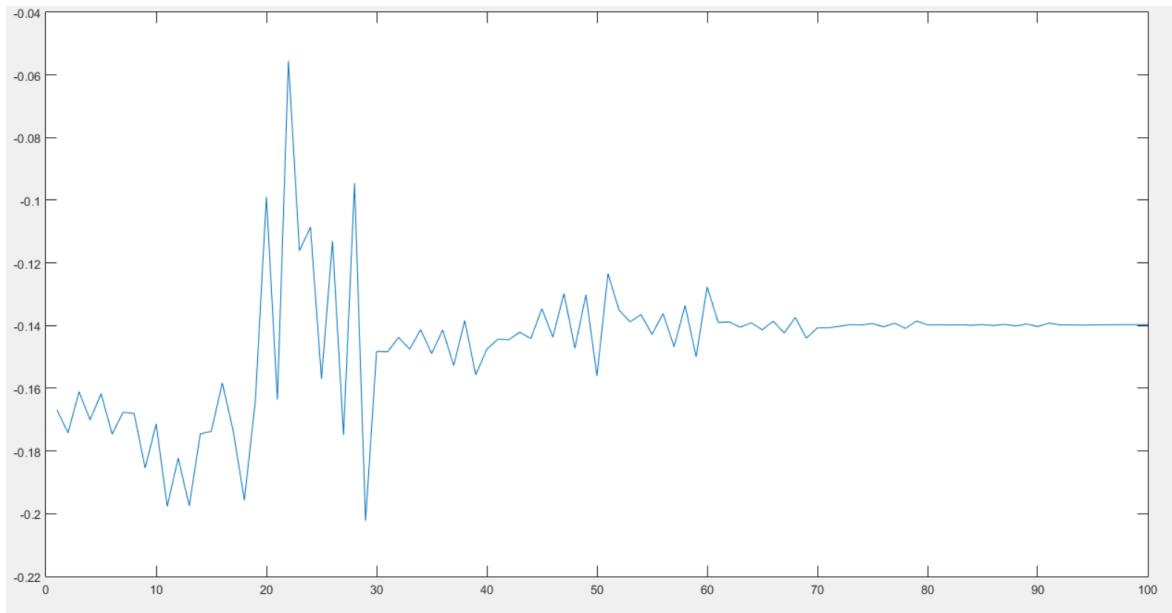


Figure 5.6: THETA BUS 4 V/S ITERATIONS

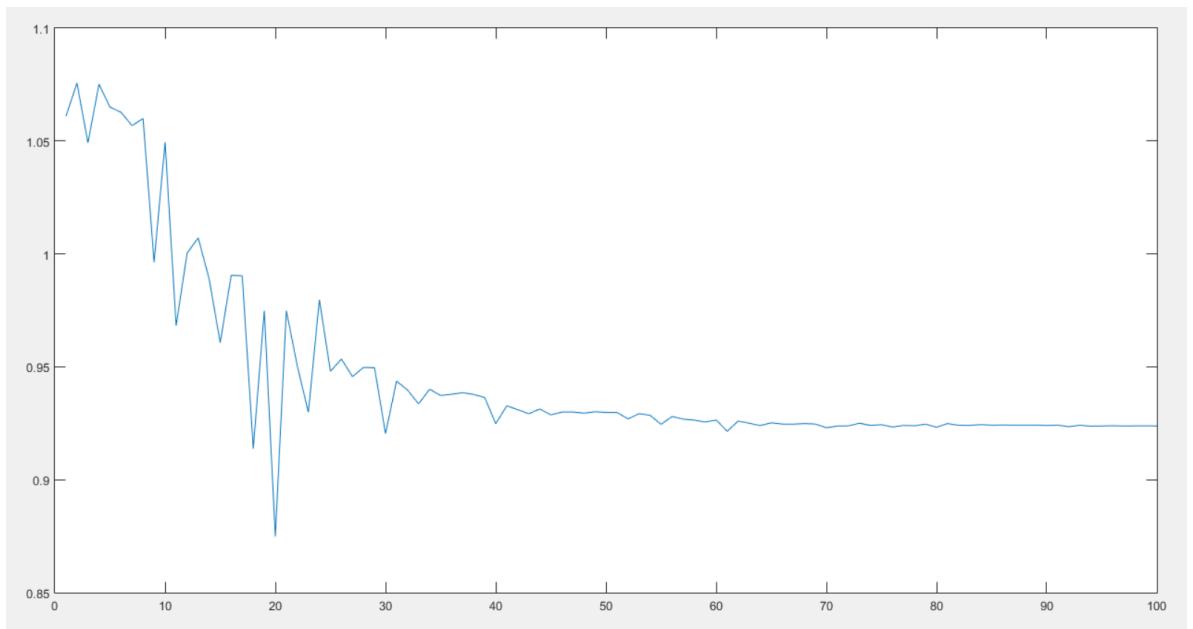


Figure 5.7: VOLTAGE BUS 4 V/S ITERATIONS

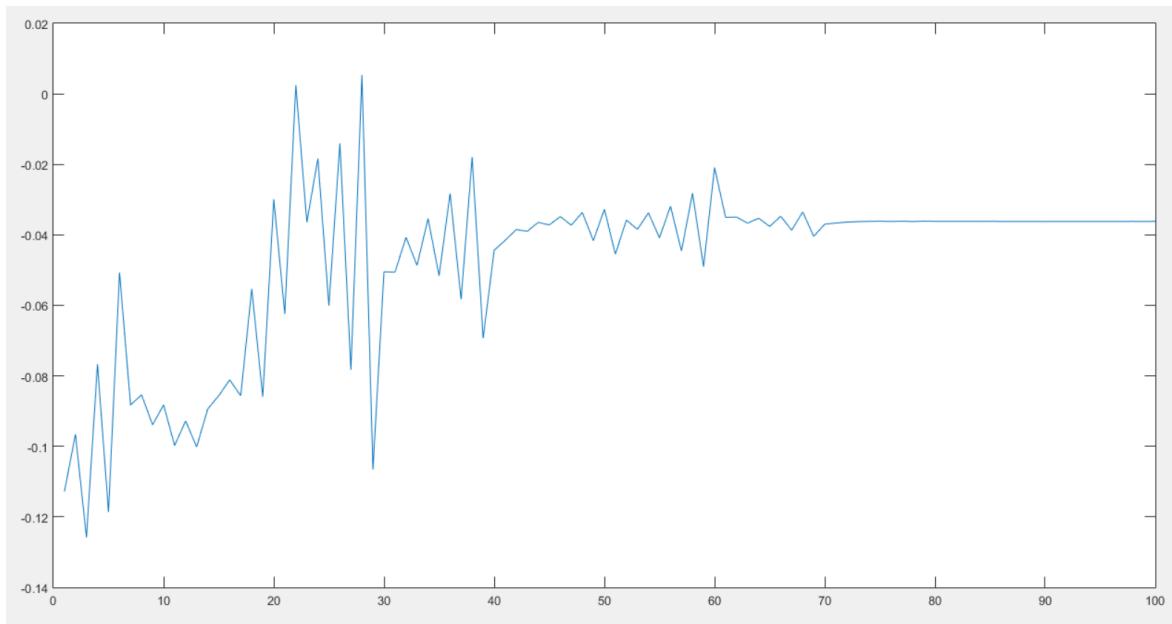


Figure 5.8: THETA BUS 5 V/S ITERATIONS

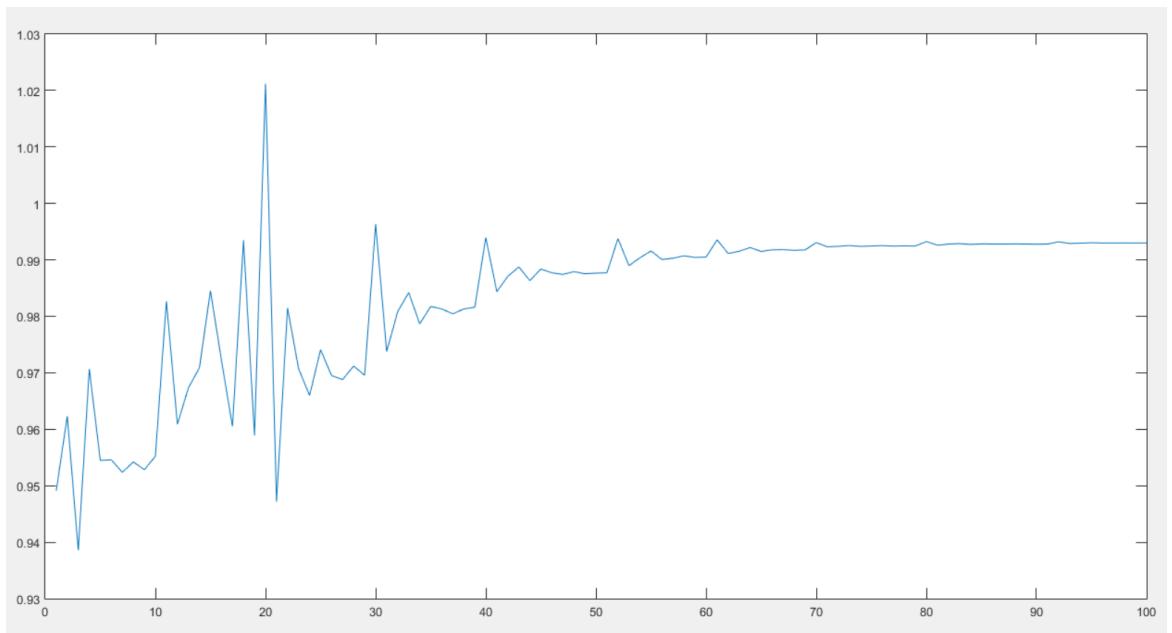


Figure 5.9: VOLTAGE BUS 5 V/S ITERATIONS

S.No	limit	S1	It	K	Injection (slack)	Injection (generator)
1	15	0.493	211	42300	65.151	99.999
2	25	0.679	230	46100	65.150	100.00
3	30	0.50	231	46300	65.151	99.999
4	45	0.85	229	45900	65.150	100.00
5	70	0.57	227	45500	65.149	100.00
6	99	0.57	213	42700	65.150	100.00
7	120	0.60	228	45700	65.150	100.00
8	150	0.50	219	43900	65.150	100.00
9	180	0.57	230	46100	65.151	99.999

Table 5.3: VARIATION OF PARAMETERS WITH DIFFERENT VALUES OF LIMIT AND S1

The original program without the improvements gave the result in 258 iterations with the objective function being calculated 51700 times



Figure 5.10: COMPARISON OF KOUNT VALUE OBTAINED IN IMPROVED PSO AND NORMAL PSO

### **5.3 Conclusion**

After comparing the graphical visualization of the results for a particular particle and the observation table presented above, we can conclude that after applying the proposed improvement to the particle swarm optimization, we are getting significantly lesser number of iterations with no alteration in the result obtained.

Using the original technique, the result is obtained in 258 iterations. Whereas, using our method, after varying the values of the limit of recombination and the constant S1.the result is obtained in 211 iterations at limit=15 and S1=0.493. Thus, the optimization efficiency is improved by almost 18.2%. From the graph, we can see the particle converges towards the solution faster (lesser no. of iterations) than the original algorithm. Thus the improvement technique proves to be a worthy addition to the existing PSO algorithm.

# CHAPTER 6

## APPENDIX

---

### RosenBrock PSO

```
1
2
3 clc
4 clear
5
6 disp(' we have to minimize f = 100 * (x1^2-x2)^2+(1-x1)^2 i.e.
      rosenbrockfunction')
7 p=input('Enter the no. of particles in a swarm');
8
9 %no. of particles
10 it=input('Enter the no. of iterations');
11
12 x1=zeros(p,it);
13
14 x2=zeros(p,it);
15
16 v1=zeros(p,it);
17
18 v2=zeros(p,it);
19
20 f=zeros(p,it);
21
22 kount=0;
23
24
25 fp=zeros(1,p);
26
27
28 df=zeros(1,(it-1));
29
30 rp=0.4;
31
32
33 rg=0.1;
34
35 cp=2;
```

```

36
37 cg = 0.2
38
39 T=input('Enter the tolerance value');
40
41 % Initial values i.e. 0th iteration
42
43 x1 (:,1)=[1.2886 0.7572 1.6232 1.0657 0.7015 1.8780 1.7519 1.1003
44 %           1.2450 1.1741];
45 x2 (:,1)=[0.4155 0.6025 0.9418 0.4610 1.6886 0.3895 0.4518 0.3414
46 %           0.4553 0.8714];
47 v1 (:,1)=[0.0326 0.5612 0.8819 0.6692 0.1904 0.3689 0.4607 0.9816
48 %           0.1564 0.8555];
49 v2 (:,1)=[0.2518 0.2904 0.6171 0.2653 0.8244 0.9827 0.7302 0.3439
50 %           0.5841 0.1078];
51
52
53 i=0;
54
55 disp (sprintf('enter the values of %dth iteration positions of %d
56 %           particles for variable x1',i,p))
57
58 for j=1:p
59 x1(j,1)=input(sprintf('enter the value of x1(%d,%d)',j,i));
60 end
61
62 disp (sprintf('enter the values of 0th iteration positions of %d
63 %           particles for variable x2',p))
64
65 for j=1:p
66 x2(j,1)=input(sprintf('enter the value of x2(%d,%d)',j,i));
67 end
68
69 disp (sprintf('enter the values of 0th iteration positions of %d
70 %           particles for variable v1',p))
71
72 for j=1:p
73 v1(j,1)=input(sprintf('enter the value of v1(%d,%d)',j,i));
74 end
75
76 disp (sprintf('enter the values of 0th iteration positions of %d
77 %           particles for variable v2',p))
78
79 for j=1:p
80 f(j,1)= 100*( (x1(j,1))^2 - x2(j,1) )^2 + (1- x1(j,1))^2 ; kount=
81 %           kount+1;
82 end
83
84

```

```

85 %Initial personal besst values
86
87 x1p=x1 (:,1);
88 x2p=x2 (:,1);
89
90 %for Initial Global best values updation fmin=min(f(:,1));
91 for k=1:p
92
93 if f(k,1)==fmin
94     gb=k;
95 else
96     end
97 end
98
99 %Initial global best value
100 x1g=zeros (p);
101
102 x2g=zeros (p);
103 for k=1:p
104     x1g(k) = x1(gb,1);
105
106 x2g(k) = x2(gb,1);
107 end
108 fgm = min(f(:,1));
109
110 fig=zeros (1,485);
111
112 t=zeros (1,485);
113
114
115 for i=1:it
116     disp(sprintf('This is %d no. of iteration',i))
117
118 %for inertia weight W
119 wmax=0.9;
120 wmin=0.4;
121 w = wmax-i*((wmax-wmin)/it);
122
123 for j=1:p
124     v1(j, (i+1)) = w*v1(j, i) + rp*cp*(x1p(j)-x1(j, i)) + rg*cg*(x1g(j)-
125         x1(j, i));
126
127 v2(j, (i+1)) = w*v2(j, i) + rp*cp*(x2p(j)-x2(j, i)) + rg*cg*(x2g(j)-
128         x2(j, i));
129
130 x1(j, (i+1)) = x1(j, i) + v1(j, (i+1));
131 x2(j, (i+1)) = x2(j, i) + v2(j, (i+1));
132
133 f(j, (i+1))= 100*( (x1(j, (i+1)))^2 - x2(j, (i+1)) )^2 + (1-x1(j, (i+1)))^2 ;
134 kount=kount+1;
135
136 end
137
138 %To find change in the values of f
139
140 for j=1:p

```

```

141         df(j,i)= abs(f(j,(i+1))-f(j,i)) ;
142     end
143
144     %personal best values updation
145
146     for j=1:p
147
148         fp(j)= 100*( (x1p(j))^2 - x2p(j) )^2 + (1- x1p(j))^2 ; kount=
149             kount+1;
150
151     end
152     for k=1:p
153         if f(k,i)< fp(k)
154             x1p(k)=x1(k,i);
155             x2p(k)=x2(k,i);
156
157         else
158             end
159         end
160
161         %for Global best values updation
162
163         if min(f(:,(i+1)))<fgm
164             fgm=min(f(:,(i+1)));
165         else
166             end
167
168         for j=1:i
169             for k=1:p
170                 if f(k,i)==fgm
171
172                     for l=1:p
173
174                         x1g(l) = x1(k,i);
175
176                         x2g(l) = x2(k,i);
177
178
179
180
181
182
183             %global best values
184
185             end
186             else
187
188                 end
189             end
190         end
191
192         print = [x1(:,i) x2(:,i) v1(:,i) v2(:,i) f(:,i)];
193
194         disp('      x1      x2      v1      v2      f')
195         disp(print)
196
197         fig(i) = figure('Position', [100 100 500 350]);

```

```

198
199      t(i) = uitable('Parent', fig(i), 'Position', [25
200          25 450 200]);
201
202      print = [x1(:,i) x2(:,i) v1(:,i) v2(:,i) f(:,i)
203          ];
204      set(t(i), 'Data', print);
205      set(t(i), 'ColumnName', {'x1', 'x2', 'v1', 'v2',
206          'f'});
207
208      %Stoping criterion
209      ki=0;
210
211      for j=1:p
212
213          if (df(j,i)<=10^(-T))
214              ki=ki+1;
215
216          end
217          end
218          if ki >= p
219              break
220          end
221
222          [r,c]=find(f==fgm);
223          minf=100*( (x1g(j))^2 - x2g(1) )^2 + (1- x1g
224              (1))^2;
225          disp(sprintf('min value of function is %d and
226              at values of x1=%d and x2=%d
227              ',minf,x1g(1),x2g(1)))
228          kount+1

```

# Constant Weight PSO

```
1      clc
2      clear
3      disp(' we have to minimize f = 100(x1^2-x2)^2+(1-x1)^2 i.e.
        rosenbrockfunction')
4      p=input('Enter the no. of particles in a swarm');
5      %no. of particles
6      it=input('Enter the no. of iterations');
7      x1=zeros(p,it);
8      x2=zeros(p,it);
9      v1=zeros(p,it);
10     v2=zeros(p,it);
11     f=zeros(p,it);
12     kount=0;
13     fp=zeros(1,p);
14     df=zeros(1,(it-1));
15     rp=1;
16     rg=1;
17     cp=1;
18     cg=1;
19     T=input('Enter the tolerance value');
20     % Initial values i.e. 0th iteration
21     x1(:,1)=[1.2886 0.7572 1.6232 1.0657 0.7015 1.8780 1.7519
22           1.1003 1.2450 1.1741];
23     x2(:,1)=[0.4155 0.6025 0.9418 0.4610 1.6886 0.3895 0.4518
24           0.3414 0.4553 0.8714];
25     v1(:,1)=[0.0326 0.5612 0.8819 0.6692 0.1904 0.3689 0.4607
26           0.9816 0.1564 0.8555];
27     v2(:,1)=[0.2518 0.2904 0.6171 0.2653 0.8244 0.9827 0.7302
28           0.3439 0.5841 0.1078];
29     %0.9063 0.8797 0.8178 0.2607 0.5944 0.0225 0.4253 0.3127
30           0.1615 0.1788];
31     x1(:,1)=unifrnd(0,2,1,p);
32     x2(:,1)=unifrnd(0,2,1,p);
33     v1(:,1)=rand(1,p);
34     v2(:,1)=rand(1,p);
35     i=0;
36     disp (sprintf('enter the values of %dth iteration
            positions of %d particles for variable x1',i,p))
37     for j=1:p
38         x1(j,1)=input(sprintf('enter the value of x1(%d,%d)',j,i)
39             );
40     end
41     disp (sprintf('enter the values of 0th iteration
            positions of %d particles for variable x2',p))
42     for j=1:p
43         x2(j,1)=input(sprintf('enter the value of x2(%d,%d)',j,i)
44             );
45     end
46     disp (sprintf('enter the values of 0th iteration positions of
            %d particles for variable v1',p))
47     for j=1:p
48         v1(j,1)=input(sprintf('enter the value of v1(%d,%d)',j,i)
49             );
50     end
51     disp (sprintf('enter the values of 0th iteration
```

```

        positions of %d particles for variable v2',p))
44    for j=1:p
45        v2(j,1)=input(sprintf('enter the value of v2(%d,%d)',j,i)
46            );
47        end
48        for j=1:p
49            f(j,1)= 100*( (x1(j,1))^2 - x2(j,1) )^2 + (1- x1(j,1))^2 ;
50            kount=kount+1;
51        end
52        %Initial personal besst values
53        x1p=x1(:,1);
54        x2p=x2(:,1);
55        %for Initial Global best values updation fmin=min(f(:,1));
56        for k=1:p
57            if f(k,1)==fmin
58                gb=k;
59            else
60            end
61            %Initial global best value
62            x1g=zeros(p);
63            x2g=zeros(p);
64            for k=1:p
65                x1g(k) = x1(gb,1);
66                x2g(k) = x2(gb,1);
67            end
68            fgm = min(f(:,1));
69            fig=zeros(1,485);
70            t=zeros(1,485);
71            for i=1:it
72                disp(sprintf('This is %d no. of iteration',i))
73                %for inertia weight W
74                w=0.6
75                for j=1:p
76                    v1(j,(i+1)) = w*v1(j,i) + rp*cp*(x1p(j)-x1(j,i)) + rg*cg*(x1g
77                        (j)-
78                        x1(j,i));
79                    v2(j,(i+1)) = w*v2(j,i) + rp*cp*(x2p(j)-x2(j,i)) + rg*cg*(x2g
80                        (j)-
81                        x2(j,i));
82                    x1(j,(i+1)) = x1(j,i) + v1(j,(i+1));
83                    x2(j,(i+1)) = x2(j,i) + v2(j,(i+1));
84                    f(j,(i+1))= 100*( (x1(j,(i+1)))^2 - x2(j,(i+1) )^2 + (1-x1(j
85                        ,(i+1)))^2 ;
86                    kount=kount+1;
87                end
88                %To find change in the values of f
89                for j=1:p
90                    df(j,i)= abs(f(j,(i+1))-f(j,i)) ;
91                end
92                %personal best values updation
93                for j=1:p
94                    fp(j)= 100*( (x1p(j))^2 - x2p(j) )^2 + (1- x1p(j))^2 ; kount=

```

```

95      x2p(k)=x2(k,i);
96
97      else
98      end
99      end
100     %for Global best values updation
101     if min(f(:,(i+1)))<fgm
102     fgm=min(f(:,(i+1)));
103     else
104     end
105     for j=1:i
106     for k=1:p
107     if f(k,i)==fgm
108     for l=1:p
109     xlg(l) = x1(k,i);
110     x2g(l) = x2(k,i);
111     %global best values
112     end
113     else
114     end
115     end
116     print = [x1(:,i) x2(:,i) v1(:,i) v2(:,i) f(:,i)];
117     disp(' x1 x2 v1 v2 f')
118     disp(print)
119     fig(i) = figure('Position', [100 100 500 350]);
120     t(i) = uitable('Parent', fig(i), 'Position', [25 25 450
121         200]);
122     print = [x1(:,i) x2(:,i) v1(:,i) v2(:,i) f(:,i)];
123     set(t(i), 'Data', print);
124     set(t(i), 'ColumnName', {'x1', 'x2', 'v1', 'v2', 'f'});
125     %Stoping criterion
126     ki=0;
127     for j=1:p
128     if (df(j,i)<=10^(-T))
129     ki=ki+1;
130     end
131     if ki >= p
132     break
133     end
134     end
135     [r,c]=find(f==fgm);
136     minf=100*( (xlg(j))^2 - x2g(1) )^2 + (1- xlg(1))^2;
137     disp(sprintf('min value of function is %d and at values of x1
138         =%d and x2=%d
139         ,minf,xlg(1),x2g(1)))
140         kount+1
141         for m=1:p
142         figure(m)
143         subplot(2,1,1)
144         plot(x1(m,1:i),x2(m,1:i))
145         hold on
146         plot(x1(m,1),x2(m,1), 'r*')
147         hold on
148         plot(x1(m,i),x2(m,i), 'o')
149         hold on
150         end

```

# Positional PSO

```
1 clc
2 clear
3 disp(' we have to minimize f = 100(x1^2-x2)^2+(1-x1)^2 i.e.
      rosenbrock
4 function')
5 p=input('Enter the no. of particles in a swarm');
6 %no. of particles
7 it=input('Enter the no. of iterations');
8 x1=zeros(p,it);
9 x2=zeros(p,it);
10 v1=zeros(p,it);
11 v2=zeros(p,it);
12 f=zeros(p,it);
13 kount=0;
14 fp=zeros(1,p);
15 df=zeros(1,(it-1));
16 rp=1;
17 rg=1;
18 cp=1;
19 cg=1;
20 T=input('Enter the tolerance value');
21 % Initial values i.e. 0th iteration
22 x1(:,1)=[1.2886 0.7572 1.6232 1.0657 0.7015 1.8780 1.7519 1.1003
           1.2450 1.1741];
23 x2(:,1)=[0.4155 0.6025 0.9418 0.4610 1.6886 0.3895 0.4518 0.3414
           0.4553 0.8714];
24 v1(:,1)=[0.0326 0.5612 0.8819 0.6692 0.1904 0.3689 0.4607 0.9816
           0.1564 0.8555];
25 %0.6448 0.3763 0.1909 0.4283 0.4820 0.1206 0.5895 0.2262 0.3846
           0.5830];
26 v2(:,1)=[0.2518 0.2904 0.6171 0.2653 0.8244 0.9827 0.7302 0.3439
           0.5841
           0.1078];
27 %0.9063 0.8797 0.8178 0.2607 0.5944 0.0225 0.4253 0.3127 0.1615
           0.1788];
28         x1(:,1)=unifrnd(0,2,1,p);
29         x2(:,1)=unifrnd(0,2,1,p);
30         v1(:,1)=rand(1,p);
31         v2(:,1)=rand(1,p);
32         % i=0;
33         disp (sprintf('enter the values of %dth iteration positions of %
            d particles for variable x1',i,p))
34         for j=1:p
35             x1(j,1)=input(sprintf('enter the value of x1(%d,%d)',j,i));
36         end
37         disp (sprintf('enter the values of 0th iteration positions of %d
            particles for variable x2',p))
38         for j=1:p
39             x2(j,1)=input(sprintf('enter the value of x2(%d,%d)',j,i));
40         end
41         disp (sprintf('enter the values of 0th iteration positions of %d
            particles for variable v1',p))
42         for j=1:p
43             v1(j,1)=input(sprintf('enter the value of v1(%d,%d)',j,i));
44         end
```

```

46     disp (sprintf('enter the values of 0th iteration positions of %d
47         particles for variable v2',p))
48     for j=1:p
49         v2(j,1)=input(sprintf('enter the value of v2(%d,%d)',j,i));
50         end
51     for j=1:p
52         f(j,1)= 100*( (x1(j,1))^2 - x2(j,1) )^2 + (1- x1(j,1))^2 ; kount=
53         kount+1;
54     end
55     %Initial personal besst values
56     x1p=x1(:,1);
57     x2p=x2(:,1);
58     %for Initial Global best values updation fmin=min(f(:,1));
59     for k=1:p
60         if f(k,1)==fmin
61             gb=k;
62         else
63             end
64         %Initial global best value
65         x1g=zeros(p);
66         x2g=zeros(p);
67         for k=1:p
68             x1g(k) = x1(gb,1);
69             x2g(k) = x2(gb,1);
70         end
71         fgm = min(f(:,1));
72         fig=zeros(1,485);
73         t=zeros(1,485);
74         i=1;
75         lim=14;
76         for iter=1:it
77             disp(sprintf('This is %d no. of iteration',iter))
78             if iter==lim+1
79                 fold=f(:,1:lim);
80                 x1old(:,1:lim)=x1(:,1:lim);
81                 x2old(:,1:lim)=x2(:,1:lim);
82                 x1new=zeros(p,it-lim);
83                 x2new=zeros(p,it-lim);
84                 for par=1:p
85                     x1new(par,1)=(sum(x1(par,1:i).*f(par,1:i)).^-1)/sum(f(par,1:i).^-1);
86                     x2new(par,1)=(sum(x2(par,1:i).*f(par,1:i)).^-1)/sum(f(par,1:i).^-1);
87                 end
88                 x1=x1new;
89                 x2=x2new;
90             %v1(:,1)=[0.0326 0.5612 0.8819 0.6692 0.1904 0.3689 0.4607 0.9816
91             %          0.1564 0.8555];
92             %v2(:,1)=[0.2518 0.2904 0.6171 0.2653 0.8244 0.9827 0.7302 0.3439
93             %          0.5841 0.1078];
94             v1=zeros(p,it-lim);
95             v2=zeros(p,it-lim);
96             f=zeros(p,it-lim);
97             fp=zeros(1,p);
98             df=zeros(1,(it-1-lim));
99             for j=1:p
100                 f(j,1)= 100*( (x1(j,1))^2 - x2(j,1) )^2 + (1- x1(j,1))^2 ; kount=

```

```

        kount+1;
100 end
101 %Initial personal besst values
102 x1p=x1(:,1);
103 x2p=x2(:,1);
104 %for Initial Global best values updation fmin=min(f(:,1));
105 for k=1:p
106 if f(k,1)==fmin
107 gb=k;
108 else
109 end
110 end
111 %Initial global best value
112 x1g=zeros(p);
113 x2g=zeros(p);
114 for k=1:p
115 x1g(k) = x1(gb,1);
116 x2g(k) = x2(gb,1);
117 end
118 fgm = min(f(:,1));
119 fig=zeros(1,485);
120 t=zeros(1,485);
121 i=1;
122 end
123 %for inertia weight W
124 w=0.6
125 for j=1:p
126 v1(j,(i+1)) = w*v1(j,i) + rp*cp*(x1p(j)-x1(j,i)) + rg*cg*(x1g(j)-x1(j,i));
127 v2(j,(i+1)) = w*v2(j,i) + rp*cp*(x2p(j)-x2(j,i)) + rg*cg*(x2g(j)-x2(j,i));
128 x1(j,(i+1)) = x1(j,i) + v1(j,(i+1));
129 x2(j,(i+1)) = x2(j,i) + v2(j,(i+1));
130 f(j,(i+1))= 100*( (x1(j,(i+1)))^2 - x2(j,(i+1)) )^2 + (1-x1(j,(i+1)))^2 ;
131 kount=kount+1;
132 end
133 %To find change in the values of f
134 for j=1:p
135 df(j,i)= abs(f(j,(i+1))-f(j,i)) ;
136 end
137 %personal best values updation
138 for j=1:p
139 fp(j)= 100*( (x1p(j))^2 - x2p(j) )^2 + (1- x1p(j))^2 ; kount=kount+1;
140 end
141 for k=1:p
142 if f(k,i)< fp(k)
143 x1p(k)=x1(k,i);
144 x2p(k)=x2(k,i);
145 else
146 end
147 end
148 %for Global best values updation
149 if min(f(:,(i+1)))<fgm
150 fgm=min(f(:,(i+1)));
151 else
152 end
153     for j=1:i

```

```

154 for k=1:p
155 if f(k,i)==fgm
156 for l=1:p
157     x1g(l) = x1(k,i);    %global best values
158 x2g(l) = x2(k,i);
159 end
160 else
161     end
162 end
163 end
164 print = [x1(:,i) x2(:,i) v1(:,i) v2(:,i) f(:,i)];
165 disp(' x1      x2      v1      v2      f')
166 disp(print)
167 fig(i) = figure('Position', [100 100 500 350]);
168 t(i) = uitable('Parent', fig(i), 'Position', [25 25 450 200]);
169 print = [x1(:,i) x2(:,i) v1(:,i) v2(:,i) f(:,i)];
170 set(t(i), 'Data', print);
171 set(t(i), 'ColumnName', {'x1', 'x2', 'v1', 'v2', 'f'});
172 %Stoping criterion
173 ki=0;
174 for j=1:p
175 if (df(j,i)<=10^(-T))
176 ki=ki+1;
177 end
178 end
179 if ki >= p
180 break
181 end
182 i=i+1;
183 end
184 [r,c]=find(f==fgm);
185 minf=100*( (x1g(j))^2 - x2g(1) )^2 + (1- x1g(1))^2;
186 disp(sprintf('min value of function is %d and at values of x1=%d and
187 x2=%d
188 ',minf,x1g(1),x2g(1)))
189 kount+1
190 x1all(1:p,1:lim)=x1old;
191 x1all(1:p,15:it)=x1;
192 x2all(1:p,1:lim)=x2old;
193 x2all(1:p,15:it)=x2;
194 fall(1:p,1:lim)=fold;
195 fall(1:p,15:it)=f;
196 for m=1:p
197 figure(m)
198 subplot(2,1,1)
199 plot(x1all(m,1:iter),x2all(m,1:iter))
200 hold on
201 plot(x1all(m,1),x2all(m,1),'r*')
202 hold on
203 plot(x1all(m,i),x2all(m,i),'o')
204 hold on
205 subplot(2,1,2)
206 plot(1:iter,fall(m,1:iter))
207 hold on
208 end

```

# PSO APPLIED TO ANALYSIS OF LOAD FLOW STUDIES

```

1 clear all
2 clc
3 kount=0;
4 nbus = 5;
5 busd = busdatas(nbus);          % Calling busdatas..
6 Y = ybusppg(nbus);            % Calling ybusppg.m to get Y-Bus Matrix..
7 BMva=100;                      % Base MVA..
8 Ql = busd(:,8)/BMva;          % load reactive power
9 Pl = busd(:,7)/BMva;          % load real power
10 Qg = busd(:,6)/BMva;         % generated reactive power.
11 Pg = busd(:,5)/BMva;          % gen erated real power
12 Qlim1 =busd(:,9)/BMva;
13 Qlim2 =busd(:,10)/BMva;
14 Q =Qg - Ql;                  % Qi =QGi - QLi
15 P =Pg - Pl;                  % Pi =PGi - PLi
16 Qsp = Q ;                    % Q--> specified
17 Psp = P ;                    % P-->Specified..
18 Qmin=Qlim1(3);
19 Qmax=Qlim2(3);
20 B =imag(Y)                   % Suscept. matrix
21 G =real(Y)                   % Conduct. matrix
22
23 %-----PSO PARAMETERS INITIALIZATION -----
24 p=100;                         % no of particle
25 it=1000;
26 rp=1.1;
27 T=14;
28 rg=1.1;
29 rf=1;
30 f=zeros(p,it);
31 fp=zeros(p,1);
32 thp=zeros(p,5);
33 thg=zeros(p,5);
34 vp=zeros(p,5);
35 vg=zeros(p,5);
36 v=zeros(p,it,5);
37 th=zeros(p,it,5);
38 vth=zeros(p,it,5);
39 vv=zeros(p,it,5);
40 a=.05;
41 b=-0.05;
42 vth(:,:,1)=a+(b-a)*rand(p,5); %initial velocity of theta vector%
43 a=.05;
44 b=-0.05;
45 vv(:,:,1)=a+(b-a)*rand(p,5); %initial velocity of voltage vector%
46 vth(:,:,1)=0;
47 vv(:,:,1)=0;
48 a=0.5;
49 b=-0.5;
50 th(:,:,1)=a+(b-a)*rand(p,5);
51 a=1.1;
52 b=0.9;
53 v(:,:,1)=a+(b-a)*rand(p,5);

```

```

54 v(:,:,1)=1.02;
55 v(:,:,3)=1.04;
56 th(:,:,1)=0;
57 vg(:,:,1)=1.02;
58 vp(:,:,1)=1.02;
59 vg(:,:,3)=1.04;
60 vp(:,:,3)=1.04;
61 thp(:,:,1)=0;
62 thg(:,:,1)=0;
63 %-----initial value of objective function
64 % Calc. P & Q
65 PVIND=zeros(p,1);
66
67 for j=1:p
68 Q =zeros(nbus,1);
69 P =zeros(nbus,1);
70 MPS=zeros(p,1);
71 MQS=zeros(p,1);
72
73 for i = 2:nbus
74     for k = 1:nbus
75         P(i) =P(i)+v(j,1,i)* v(j,1,k)*(G(i,k)*cos(th(j,1,i)-th(j
76             ,1,k)) + B(i,k)*sin(th(j,1,i)-th(j,1,k)));
77     end
78 end
79
80 for i = 2:nbus
81     for k = 1:nbus
82         Q(i) =Q(i)+v(j,1,i)* v(j,1,k)*(G(i,k)*sin(th(j,1,i)-th(j
83             ,1,k)) - B(i,k)*cos(th(j,1,i)-th(j,1,k)));
84     end
85 end
86 % real power mismatch
87 MP=P-Psp;
88 MPS=MP.^2;
89 %reactive power mismatch in third bus
90 Qsp(3)=Q(3);
91 if Q(3)<Qmin;
92     Q(3)=Qmin;
93     PVIND(j,1)=1;
94 else PVIND(j,1)=0;
95 end
96 if Q(3)>Qmax;
97     Q(3)=Qmax;
98     PVIND(j,1)=1;
99 else PVIND(j,1)=0;
100 end
101
102 %reactive power mismatch
103 MQ=Q-Qsp;
104 MQ(3)=0;
105 MQS=MQ.^2;
106 %objective function value
107 f(j,1)=sum(MPS)+sum(MQS);
108 kount=kount+1;

```

```

109 end
110
111 %Initial personal best values
112 for i=1:p
113     for k=2:5
114         thp(i,k)=th(i,1,k);
115     end
116     for k=2:5
117         vp(i,k)=v(i,1,k);
118     end
119 end
120 %for Initial Global best values updation
121 fmin=min(f(:,1));
122 for k=1:p
123     if f(k,1)==fmin
124         gb=k;
125     else
126     end
127 end
128 %Initial global best value
129
130 for k=1:p
131     for j=2:5
132         thg(k, j)=th(gb, 1, j);
133     end
134     for j=2:5
135         vg(k, j)=v(gb, 1, j);
136     end
137 end
138 fgm = min(f(:,1));
139 Q3=zeros(p,it);
140 for i=1:it
141     %for inertia weight W
142     wmax=.4;
143     wmin=.4;
144     w=wmax-((wmax-wmin)*i/it);
145     %w =0.1+(rand()/2);
146     %velocity update
147     %position update
148     for j=1:p
149         for k=2:5
150
151             vth(j, (i+1), k) = w*vth(j, i, k) + rp*(thp(j, k)-th(j, i, k)) + rg
152                 *(thg(j, k)-th(j, i, k));
153             % if vth(j, i+1 ,k)<-0.1
154             %    vth(j, i+1 ,k)=-0.1;
155             %end
156             %if vth(j, i+1 ,k)>0.1
157             %    vth(j, i+1 ,k)=0.1;
158             %end
159             th(j, (i+1), k) = th(j, i, k) + rf*vth(j, (i+1), k);
160         end
161
162         for q=2:5
163             vv(j, (i+1), q) = w*vv(j, i, q) + rp*(vp(j, q)-v(j, i, q)) + rg*(vg(
164                 j, q)-v(j, i, q));
165             if vv(j, (i+1), q)<-0.1

```

```

165             vv(j, (i+1), q)=-0.1;
166         end
167         if vv(j, (i+1), q)>0.1
168             vv(j, (i+1), q)=0.1;
169         end
170
171     v(j, (i+1), q) = v(j, i, q) + rf*vv(j, (i+1), q);
172 end
173 for q=3
174     if PVIND(j, 1)==0
175         v(j, (i+1), q)=1.04;
176     end
177 end
178
179
180 end
181
182
183 %th(:,i,5)
184
185 %objective function value
186 for j=1:p
187     Q = zeros(nbus,1);
188     P=zeros(nbus,1);
189     MPS= zeros(p,1);
190     MQS= zeros(p,1);
191
192     for m = 2:nbus
193         for k = 1:nbus
194             P(m) =P(m)+v(j, (i+1),m)* v(j, (i+1),k)* (G(m,k)*cos(th(j, (i
195                 +1),m)-th(j, (i+1),k)) + B(m,k)*sin(th(j, (i+1),m)-th(j
196                 , (i+1),k)));
197
198         end
199     end
200     for m = 2:5
201         for k = 1:nbus
202             Q(m) =Q(m) + v(j, (i+1),m)* v(j, (i+1),k)* (G(m,k)*sin(th(j
203                 , (i+1),m)-th(j, (i+1),k)) - B(m,k)*cos(th(j, (i+1),m)-th
204                 (j, (i+1),k)));
205
206         end
207     end
208
209     % real power mismatch
210     MP=P-Psp;
211     MPS=MP.^2;
212
213     %reactive power mismatch in third bus
214     Qsp(3)=Q(3);
215     if Q(3)<Qmin;
216         Q(3)=Qmin;
217         PVIND(j, 1)=1;
218     else PVIND(j, 1)=0;
219     end
220     if Q(3)>Qmax;
221         Q(3)=Qmax;
222         PVIND(j, 1)=1;
223     else PVIND(j, 1)=0;
224     end

```

```

219 Q3(j,i)=Q(3);
220 %reactive power mismatch
221 MQ=Q-Qsp;
222 MQ(3)=0;
223 MQS=MQ.^2;
224 %objective function value
225
226 f(j,(i+1))=sum(MPS)+sum(MQS);
227 kount=kount+1;
228
229
230 end
231 %personal best values updatio
232 for j=1:p
233 Q = zeros(nbus,1);
234 P =zeros(nbus,1);
235 MPS=zeros(p,1);
236 MQS=zeros(p,1);
237 for t =2:nbus
238 for k = 1:nbus
239 P(t) =P(t)+vp(j,t)* vp(j,k)*(G(t,k)*cos(thp(j,t)-thp(j,k)
240 ) + B(t,k)*sin(thp(j,t)-thp(j,k)));
241 end
242 end
243 for t = 2:nbus
244 for k = 1:nbus
245 Q(t) =Q(t) + vp(j,t)* vp(j,k)*(G(t,k)*sin(thp(j,t)-thp(j,
246 k)) - B(t,k)*cos(thp(j,t)-thp(j,k)));
247 end
248 end
249
250 % real power mismatch
251 MP=P-Psp;
252 MPS=MP.^2;
253 %reactive power mismatch in third bus
254 Qsp(3)=Q(3);
255 if Q(3)<Qmin;
256 Q(3)=Qmin;
257 PVIND(j,1)=1;
258 else PVIND(j,1)=0;
259 end
260 if Q(3)>Qmax;
261 Q(3)=Qmax;
262 PVIND(j,1)=1;
263 else PVIND(j,1)=0;
264 end
265
266 %reactive power mismatch
267 MQ=Q-Qsp;
268 MQ(3)=0;
269 MQS=MQ.^2;
270 %objective function value
271 %objective function value
272 fp(j)=sum(MPS)+sum(MQS);
273 kount=kount+1;
274 end

```

```

275 %personal best value updation
276     for k=1:p
277         for m=2:5
278             if f(k,i)<fp(k)
279                 thp(k,m)=th(k,i,m);
280             else
281                 end
282             end
283         end
284     end
285
286     for k=1:p
287         for m=2:5
288             if f(k,i)<fp(k)
289                 else
290                     vp(k,m)=v(k,i,m);
291                 end
292             end
293         end
294     end
295
296
297 %for Global best values updation
298 if min(f(:,(i+1)))<fgm
299     fgm=min(f(:,(i+1)));
300 else
301 end
302
303 for m=2:5
304
305     for k=1:p
306         if f(k,i)==fgm
307             for l=2:p
308                 thg(l,m) = th(k,i,m);      %global best values
309                 end
310             else
311                 end
312         end
313     end
314 end
315     for m=2:5
316
317         for k=1:p
318             if f(k,i)==fgm
319                 for l=2:p
320                     vg(l,m) = v(k,i,m);      %global best values
321                 end
322             else
323                 end
324         end
325     end
326 end
327
328
329 % print = [th(:,i,1) th(:,i,2) th(:,i,3) th(:,i,4) th(:,i,5) v(:,i
330 ,1) v(:,i,2) v(:,i,3) v(:,i,4) v(:,i,4) f(:,i)];
331 i
332 f(gb,i)

```

```

332    %      disp(' th1          th2          th3          th4          th5          v1
333                                v2           v3           v4           v5           f' )
334    % disp(print)
335
336        %stopping
337        gbl=gb;
338    for k=1:p
339        if f(k,1+1)==fgm
340            gbl=k;
341        else
342        end
343    end
344        if (f(gbl,i+1)<=10^(-T))
345
346            break
347        end
348
349    vth(gbl,(i+1),2);
350    end
351    %Q3(:,it)
352    bus=zeros(5,10) ;
353    bus(1,3)=v(gb,i,1);
354    bus(2,3)=v(gb,i,2);
355    bus(3,3)=v(gb,i,3);
356    bus(4,3)=v(gb,i,4);
357    bus(5,3)=v(gb,i,5);
358    %bus angle updation
359    bus(1,4)=th(gb,i,1);
360    bus(2,4)=th(gb,i,2);
361    bus(3,4)=th(gb,i,3);
362    bus(4,4)=th(gb,i,4);
363    bus(5,4)=th(gb,i,5);
364    bus(3,6)=Q3(gbl,it)*BMva;
365    x=bus(3,6);
366    V = bus(:,3) ;           % Specified Voltage..
367    del = bus(:,4) ; % Voltage Angle..
368    %load flow function calling
369    fprintf('kount value is %d\n',kount);
370    loadflow(nb, V, del, BMva, x);

```

### Description for above code :

1. This is the main program that performs PSO on given data in order to give the load flow results.
2. There are 5 buses in the system:
  - 1 Slack Bus( Bus 1)
  - 3 Load Buses (Bus 2,4,5)- P,Q Known
  - 1 Generator Bus (Bus 3)- P,—V— Known
3. Various parameters like Total Load, Total Generation, Net Generation (Total Gen-Total Load), bus admittance matrix are calculated. These will be used in PSO operation.
4. The variables that will be optimized by PSO are voltage magnitude (v) and voltage angle ( $\theta$ ).
5. For the PSO operation, we have taken:
  - No. of particles=100
  - Max. iterations=1000
  - Tolerance in objective function= $10^{-6}$
6. In each iteration, **v and theta** are updated in order to find P, Q values for each bus. The given or specified values of P and Q are checked against calculated P and Q values respectively and the mismatch of P values and that of Q values is calculated.
7. **The objective function is a sum of square of mismatch of Pand mismatch of Q.** Squaring is done in order to get rid of signs.
8. **The task of PSO is to minimize this objective function.** When this is done, we get the unknown values which can be used for Load Flow analysis.

## Bus Data

### busdata.m

```
1 % This function provides Initial Bus data of the system to the main
2 % program
3
4 % Bus Type      Type Description
5 % 1            Slack Bus
6 % 2            P-V Bus
7 % 3            P-Q Bus
8
9 %           | Bus | Type | Vsp | theta | PGi | QGi | PLi | QLi | Qmin |
10 %        Qmax |
11 busdat5 = [1    1     1.02   0     0     0     0     0     0     0
12          0;
13          2    3     1       0     0     0     60    30    0
14          0;
15          3    3     1.04   60    100   0     0     0     0     0
16          0;
17          4    3     1       0     0     0     40    10    0
18          0;
19          5    3     1       0     0     0     60    20    0
20          0;];
```

### Description for above code :

1. This is the part of the program that contains information regarding buses in the given power system.
2. From here voltage magnitude and angle, power generation, load, etc. are imported into main program and supporting functions for further calculations.

## Line Data

linedata.m

```
1 % This function provides Line Bus data of the system to the main
2 % program
3 function linedt =linedatas(num)
4 %
5 % | From | To | R | X | B/2 | X'mer |
6 % | Bus | Bus | pu | pu | pu | TAP (a) |
7 linedat5 = [ 1 2 .1 0.4 0 1
8 1 4 0.15 0.6 0 1
9 1 5 0.05 0.2 0 1
10 2 3 0.05 0.2 0 1
11 2 4 0.10 0.4 0 1
12 3 5 0.05 0.2 0 1];
13
14 linedt = linedat5;
```

**Description for above code :**

1. This part contains information regarding transmission line joining the buses in the given power system.
2. From here data required for calculation of bus admittance matrix is obtained.

# Ybus

## ybusppg.m

```
1 % This function forms and returns the Bus Admittance Matrix
2
3 function Y = ybusppg(num) % Returns Y-->bus admittance matrix
4
5 linedata = linedatas(num); % Calling Linedatas
6 x = linedata(:,4); % Reactance=X
7 r = linedata(:,3); % Resistance=R
8 z = r + i*x; % (Impedance)z matrix
9 fb = linedata(:,1); % From bus number
10 tb = linedata(:,2); % To bus number
11 a = linedata(:,6); % Tap setting value..
12 b = linedata(:,5); % Ground Admittance=B/2
13 y = 1./z; % To get inverse of each element
14 b = i*b; % Make B imaginary
15
16 nl = length(fb); % No. of branches...
17 nb = max(max(fb),max(tb)); % No. of buses
18 Y = zeros(nb,nb); % Initialise YBus
19
20 % For Off Diagonal elem
21 for k = 1:nl
22     Y(fb(k),tb(k)) = Y(fb(k),tb(k))-y(k)/a(k);
23     Y(tb(k),fb(k)) = Y(fb(k),tb(k));
24 end
25
26 % For diagonal elem
27 for m = 1:nb
28     for n = 1:nl
29         if fb(n) == m
30             Y(m,m) = Y(m,m)+y(n)/(a(n)^2) + b(n);
31         elseif tb(n) == m
32             Y(m,m) = Y(m,m)+y(n) + b(n);
33         end
34     end
35 end
```

### Description for above code :

1. This function forms the bus admittance matrix from the information present in linedatas.m

## **pol2rect**

### **pol2rect.m**

```
1 % This function converts Rectangular to Polar form
2 % [RECT]=RECT2POL(RHO, THETA)
3 % RECT= Complex matrix or number
4 % RECT = A + jB; where: A-->Real, B-->Imaginary
5 % RHO= magnitude
6 % THETA = angle(rad)
7
8 function rect =pol2rect(rho, theta)
9 rect =rho.*cos(theta)+j*rho.*sin(theta);
```

### **Description for above code :**

1. This function converts from polar coordinates to rectangular coordinates.

## loadflow

### loadflow.m

```
1 % This function takes as parameters all the final values calculated
2 % from PSO operation and also takes in values from above functions
3 % to calculate Bus current injections, Line current flows, Line
4 % power flows and Bus Power Injections.
5
6 Y =ybusppg(nb); % Calling Ybus program
7 busd =busdatas(nb); % Get busdatas..
8 lined =linedatas(nb); % Get linedats
9 nl =length(fb); % No. of Branches..
10 tb =lined(:,2); % To bus number
11 fb =lined(:,1); % From bus number
12 Del =180/pi*del; % Bus Voltage Angles in Degree
13 Vm =pol2rect(V,del); % Converting polar to rectangular
14 k1 =busd(:,2); %bus type
15 Pl =busd(:,7); % PLi..
16 Ql = busd(:,8); % QLi..
17 Pl2 = busd(:,5); % PLi..
18 Ql2 = busd(:,6); % QLi..
19 Sij = zeros(nb,nb);
20 Iij = zeros(nb,nb);
21 Si = zeros(nb,1);
22
23 % Bus Current-->Injections
24 I =Y*Vm;
25 Ia =angle(I);
26 Im =abs(I);
27
28 %Line Current
29 for m =1:nl
30     p = fb(m); q = tb(m);
31     Iij(p,q) = -(Vm(p) - Vm(q))*Y(p,q); % Y(m,n) = -y(m,n) ..
32     Iij(q,p) = -Iij(p,q);
33 end
34
35 Iij =sparse(Iij);
36 Iija =angle(Iij);
37 Iijm =abs(Iij);
38
39 % Line Power Flows..
40 for m = 1:nb
41     for n = 1:nb
42         if m ~= n
43             Sij(m,n) =Vm(m)*conj(Iij(m,n))*BMva;
44         end
45     end
46 end
47 Qij =imag(Sij);
48 Pij = real(Sij) ;
49
50
51 % Line Loss
```

```

52 Lij = zeros(nl,1);
53 for m = 1:nl
54     q = tb(m);
55     p = fb(m);
56     Lij(m) = Sij(p,q) + Sij(q,p);
57 end
58
59 Lqij = imag(Lij);
60 Lpij = real(Lij) ;
61
62 % Bus Power-->Injections
63 for i = 1:nb
64 for k = 1:nb
65     Si(i) = Si(i) + conj(Vm(i))*Vm(k)*Y(i,k)*BMva;
66 end
67 end
68 Qi = -imag(Si);
69 Pi =real(Si);
70 Pg= busd(:,5);
71 Qg= busd(:,6);
72 Pg(1)=sum(Pl)+sum(Lpij)-Pg(3);
73 Qg(3)=x;
74 Qg(1)=sum(Ql)+sum(Lqij)-Qg(3);
75
76
77 disp('
    #####');
78
79 disp('
-----');
80 disp('
PSO Loadflow Analysis ');
81
82
83 disp('
-----');
84
85 disp(' | Bus | V | Angle | Injection | Generation
      |       Load       |' );
86
87 disp(' | No | pu | Degree | MW | MVar | MW | Mvar
      | MW | MVar | ' );
88
89 for m = 1:nb
90     disp('
-----');
91     fprintf('%3g', m); fprintf(' %8.4f', V(m)); fprintf(' %8.4f',
         Del(m));
92     fprintf(' %8.3f', Pi(m)); fprintf(' %8.3f', Qi(m));
93     fprintf(' %8.3f', Pg(m)); fprintf(' %8.3f', Qg(m));
94     fprintf(' %8.3f', Pl(m)); fprintf(' %8.3f', Ql(m)); fprintf('\n');

```

```

98 end
99
100 disp('
-----');
101
102 fprintf(' Total %8.3f', sum(Pi));
103 fprintf(' %8.3f', sum(Qi));
104 fprintf(' %8.3f', sum(Pi+Pl)); fprintf(' %8.3f', sum(Qi+Ql));
105
106 fprintf(' %8.3f', sum(Pl)); fprintf(' %8.3f', sum(Ql)); fprintf('\n');
107
108 disp('
#####
#');
109
110 disp('
-----');
111 disp(' Line Flow and Losses ');
112 disp('
-----');
113 disp('|From|To | P | Q | From| To | P | Q |
Line Loss |');
114 disp('|Bus |Bus| MW | MVar | Bus | Bus| MW | MVar |
MW | MVar |');
115 for m = 1:nL
116 p = fb(m); q = tb(m);
117
118 disp('
-----');
119
120 fprintf('%4g', p); fprintf('%4g', q); fprintf(' %8.3f', Pij(p,q));
121 fprintf(' %8.3f', Qij(p,q));
122
123 fprintf('%4g', q); fprintf('%4g', p); fprintf(' %8.3f', Pij(q,p));
124 fprintf(' %8.3f', Qij(q,p));
125
126 end
127
128 disp('
-----');
129
130 fprintf(' Total Loss
');
131
132 fprintf(' %8.3f', sum(Lpij)); fprintf(' %8.3f', sum(Lqij));
133 fprintf('\n');
134 disp('
-----');

```

```
        ' ) ;  
135  
136 disp( '# #####';  
        ' ) ;  
137 clearvars -global
```

### Description for above code :

1. This function operates at the end of pso.m ie. at the end of PSO operation. takes as parameters all the final values calculated from PSO operation and also takes in values from above functions to calculate Bus current injections, Line current flows, Line power flows and Bus Power Injections. finally displays all calculated values and final load flow analysis.

# IMPROVED PSO APPLIED TO LOAD FLOW STUDIES

improvedpsom.m

```
1 clear all
2 clc
3 kount=0;
4 lim=15;
5 s1=0.493;
6 nbus = 5;
7 BMva=100; % Base MVA..
8 busd = busdatas(nbus); % Calling busdatas
9 Y = ybusppg(nbus); % Calling ybusppg.m
10 Qg =busd(:, 6)/BMva; % generated reactive power.
11 Pg =busd(:, 5)/BMva; % gen erated real power
12 Ql =busd(:, 8)/BMva; % load reactive power
13 Pl =busd(:, 7)/BMva; % load real power
14 Qlim1 = busd(:, 9)/BMva;
15 Qlim2 = busd(:, 10)/BMva;
16 Q =Qg -Ql;
17 P =Pg -Pl;
18 Qsp =Q ; % Q specified
19 Psp =P ; % P Specified
20 Qmin=Qlim1(3);
21 Qmax=Qlim2(3);
22 B =imag(Y) % Susceptance matrix..
23 G =real(Y) % Conductance matrix..
24
25 %-----PSO PARAMETERS INITIALIZATION -----
26 p=100; % no of particle
27 it=1000;
28 rp=1.1;
29 T=12;
30 rg=1.1;
31 rf=1;
32 f=zeros(p,it);
33 fp=zeros(p,1);
34 thp=zeros(p,5);
35 thg=zeros(p,5);
36 vp=zeros(p,5);
37 vg=zeros(p,5);
38 v=zeros(p,it,5);
39 th=zeros(p,it,5);
40 vth=zeros(p,it,5);
41 vv=zeros(p,it,5);
42 a=.05;
43 b=-0.05;
44 vth(:,:,1)=a+(b-a)*rand(p,5); %initial velocity of theta vector%
45 a=.05;
46 b=-0.05;
47 vv(:,:,1)=a+(b-a)*rand(p,5); %initial velocity of voltage vector%
48 vth(:,:,1)=0;
49 vv(:,:,1)=0;
50 a=0.5;
51 b=-0.5;
52 th(:,:,1)=a+(b-a)*rand(p,5);
```

```

53 a=1.1;
54 b=0.9;
55 v (:,1,:)=a+(b-a)*rand(p,5);
56 v (:,:,1)=1.02;
57 v (:,:,3)=1.04;
58 th (:,:,1)=0;
59 vg (:,1)=1.02;
60 vp (:,1)=1.02;
61 vg (:,3)=1.04;
62 vp (:,3)=1.04;
63 thp (:,1)=0;
64 thg (:,1)=0;
65 %-----initial value of objective function
-----%
66 % Calculate P and Q
67 PViND=zeros(p,1);
68
69 for j=1:p
70 Q =zeros(nbus,1);
71 P =zeros(nbus,1);
72 MPS=zeros(p,1);
73 MQS=zeros(p,1);
74
75 for i = 2:nbus
76     for k = 1:nbus
77         P(i) = P(i) + v(j,1,i)* v(j,1,k)*(G(i,k)*cos(th(j,1,i)-th
(j,1,k)) + B(i,k)*sin(th(j,1,i)-th(j,1,k)));
78     end
79 end
80
81 for i = 2:nbus
82     for k = 1:nbus
83         Q(i) = Q(i) + v(j,1,i)* v(j,1,k)*(G(i,k)*sin(th(j,1,i)-th
(j,1,k)) - B(i,k)*cos(th(j,1,i)-th(j,1,k)));
84     end
85
86 end
87
88 % real power mismatch
89 MP=P-Psp;
90 MPS=MP.^2;
91 %reactive power mismatch in third bus
92 Qsp(3)=Q(3);
93 if Q(3)<Qmin;
94     Q(3)=Qmin;
95     PViND(j,1)=1;
96 else PViND(j,1)=0;
97 end
98 if Q(3)>Qmax;
99     Q(3)=Qmax;
100    PViND(j,1)=1;
101 else PViND(j,1)=0;
102 end
103
104 %reactive power mismatch
105 MQ=Q-Qsp;
106 MQ(3)=0;
107 MQS=MQ.^2;

```

```

108 %objective function value
109 f(j,1)=sum(MPS)+sum(MQS);
110 kount=kount+1;
111 end
112
113 %Initial personal best values
114 for i=1:p
115     for k=2:5
116         thp(i,k)=th(i,1,k);
117     end
118     for k=2:5
119         vp(i,k)=v(i,1,k);
120     end
121 end
122 %for Initial Global best values updation
123 fmin=min(f(:,1));
124 for k=1:p
125     if f(k,1)==fmin
126         gb=k;
127     else
128     end
129 end
130 %Initial global best value
131
132 for k=1:p
133     for j=2:5
134         thg(k,j)=th(gb,1,j);
135     end
136     for j=2:5
137         vg(k,j)=v(gb,1,j);
138     end
139 end
140 fgm = min(f(:,1));
141 Q3=zeros(p,it);
142 for i=1:it
143     %Repositioning
144
145     %for inertia weight W
146     wmax=.4;
147     wmin=.4;
148     w=wmax-(wmax-wmin)*i/it;
149     %w =0.1+(rand()/2);
150     %velocity update
151     %position update
152     for j=1:p
153         for k=2:5
154
155             vth(j, i+1 ,k) = w*vth(j,i,k) + rp*(thp(j,k)-th(j,i,k)) + rg
156             *(thg(j,k)-th(j,i,k));
157             %
158             if vth(j, i+1 ,k)<-0.1
159             %
160                 vth(j, i+1 ,k)=-0.1;
161             %
162             if vth(j, i+1 ,k)>0.1
163                 vth(j, i+1 ,k)=0.1;
164             %
165             end
166             th(j, (i+1),k) = th(j,i,k) + rf*vth(j,(i+1),k);
167             %Repositioning
168             if i==lim+1

```

```

165      th(j,i+1,k)=(s1*th(gb,lim,k)*f(gb,lim)^-1+thp(j,k)*fp(j)
166      ^-1)/(s1*f(gb,lim)^-1+fp(j)^-1);
167    end
168  end
169
170  for q=2:5
171    vv(j,(i+1),q) = w*vv(j,i,q) + rp*(vp(j,q)-v(j,i,q)) + rg*(vg(
172      j,q)-v(j,i,q));
173    if vv(j,(i+1),q)<-0.1
174      vv(j,(i+1),q)=-0.1;
175    end
176    if vv(j,(i+1),q)>0.1
177      vv(j,(i+1),q)=0.1;
178    end
179
180    v(j,(i+1),q) = v(j,i,q) + rf*vv(j,(i+1),q);
181    %Repositioning
182    if i==lim+1
183      th(j,i+1,k)=(s1*th(gb,lim,k)*f(gb,lim)^-1+thp(j,k)*fp(j)
184      ^-1)/(s1*f(gb,lim)^-1+fp(j)^-1);
185    end
186    for q=3
187      if PVIND(j,1)==0
188        v(j,(i+1),q)=1.04;
189    end
190  end
191
192 end
193
194
195 %th(:,i,5)
196
197 %objective function value
198 for j=1:p
199   Q=zeros(nbus,1);
200   P=zeros(nbus,1);
201   MPS=zeros(p,1);
202   MQS=zeros(p,1);
203
204   for m =2:nbus
205     for k =1:nbus
206       P(m) =P(m) + v(j,(i+1),m)* v(j,(i+1),k)*(G(m,k)*cos(th(j
207         ,(i+1),m)-th(j,(i+1),k)) + B(m,k) * sin(th(j,(i+1),m)-
208         th(j,(i+1),k)));
209     end
210   end
211   for m = 2:5
212     for k = 1:nbus
213       Q(m) =Q(m) + v(j,(i+1),m)* v(j,(i+1),k)*(G(m,k)*sin(th(j
214         ,(i+1),m)-th(j,(i+1),k)) - B(m,k)*cos(th(j,(i+1),m)-th
215         (j,(i+1),k)));
216   end
217 end

```

```

216 % real power mismatch
217 MP=P-Psp;
218 MPS=MP.^2;
219 %reactive power mismatch in third bus
220 Qsp(3)=Q(3);
221 if Q(3)<Qmin;
222 Q(3)=Qmin;
223 PVIND(j,1)=1;
224 else PVIND(j,1)=0;
225 end
226 if Q(3)>Qmax;
227 Q(3)=Qmax;
228 PVIND(j,1)=1;
229 else PVIND(j,1)=0;
230 end
231 Q3(j,i)=Q(3);
232 %reactive power mismatch
233 MQ=Q-Qsp;
234 MQ(3)=0;
235 MQS=MQ.^2;
236 %objective function value
237
238 f(j, (i+1))=sum(MPS)+sum(MQS);
239 kount=kount+1;
240
241
242 end
243 %personal best values updatio
244 for j=1:p
245 Q=zeros(nbus,1);
246 P=zeros(nbus,1);
247 MPS=zeros(p,1);
248 MQS=zeros(p,1);
249 for t =2:nbus
250 for k = 1:nbus
251 P(t) = P(t) + vp(j,t)* vp(j,k)*(G(t,k)*cos(thp(j,t)-thp(j,k)) + B(t,k)*sin(thp(j,t)-thp(j,k)));
252
253 end
254 end
255 for t = 2:nbus
256 for k = 1:nbus
257 Q(t) = Q(t) + vp(j,t)* vp(j,k)*(G(t,k)*sin(thp(j,t)-thp(j,k)) - B(t,k)*cos(thp(j,t)-thp(j,k)));
258
259 end
260 end
261
262 % real power mismatch
263 MP=P-Psp;
264 MPS=MP.^2;
265 %reactive power mismatch in third bus
266 Qsp(3)=Q(3);
267 if Q(3)<Qmin;
268 Q(3)=Qmin;
269 PVIND(j,1)=1;
270 else PVIND(j,1)=0;
271 end

```

```

272     if Q(3)>Qmax;
273         Q(3)=Qmax;
274         PVIND(j,1)=1;
275     else PVIND(j,1)=0;
276     end
277
278 %reactive power mismatch
279 MQ=Q-Qsp;
280 MQ(3)=0;
281 MQS=MQ.^2;
282 %objective function value
283 %objective function value
284 fp(j)=sum(MPS)+sum(MQS);
285 kount=kount+1;
286 end
287 %personal best value updation
288 for k=1:p
289     for m=2:5
290         if f(k,i)<fp(k)
291             thp(k,m)=th(k,i,m);
292         else
293             end
294
295     end
296
297     end
298
299     for k=1:p
300         for m=2:5
301             if f(k,i)<fp(k)
302                 else
303                     vp(k,m)=v(k,i,m);
304                 end
305
306             end
307         end
308
309 %for Global best values updation
310 if min(f(:,(i+1)))<fgm
311     fgm=min(f(:,(i+1)));
312 else
313 end
314
315 for m=2:5
316
317     for k=1:p
318         if f(k,i)==fgm
319             for l=2:p
320                 thg(l,m) = th(k,i,m);      %global best values
321                 end
322             else
323             end
324
325         end
326     end
327     for m=2:5
328
329         for k=1:p

```

```

330      if f(k,i)==fgm
331          for l=2:p
332              vg(l,m) = v(k,i,m);           %global best values
333          end
334      else
335      end
336
337  end
338 end
339
340
341 % print = [th(:,i,1) th(:,i,2) th(:,i,3) th(:,i,4) th(:,i,5) v(:,i
342 ,1) v(:,i,2) v(:,i,3) v(:,i,4) v(:,i,4) f(:,i)]; 
343 i
344 f(gb,i)
345 % disp(' th1      th2      th3      th4      th5      v1
346 %           v2      v3      v4      v5      f' )
347
348 % disp(print)
349
350
351 gbl=gb;
352 for k=1:p
353     if f(k,1+1)==fgm
354         gbl=k;
355     else
356     end
357     if (f(gbl,i+1)<=10^(-T))
358
359         break
360     end
361
362 vth(gbl,(i+1),2);
363 end
364 %Q3(:,it)
365 bus=zeros(5,10) ;
366 bus(1,3)=v(gb,i,1);
367 bus(2,3)=v(gb,i,2);
368 bus(3,3)=v(gb,i,3);
369 bus(4,3)=v(gb,i,4);
370 bus(5,3)=v(gb,i,5);
371 %bus angle updation
372 bus(1,4)=th(gb,i,1);
373 bus(2,4)=th(gb,i,2);
374 bus(3,4)=th(gb,i,3);
375 bus(4,4)=th(gb,i,4);
376 bus(5,4)=th(gb,i,5);
377 bus(3,6)=Q3(gb1,it)*BMva;
378 x=bus(3,6);
379 V = bus(:,3) ;           % Specified Voltage..
380 del = bus(:,4) ; % Voltage Angle..
381 %load flow function calling
382 fprintf('kount value is %d\n',kount);
383 loadflow(nbustest,V,del,BMva,x);

```

# References

1. Butt, Azhar Iqbal Kashif. "Optimal Control of Tube Drawing Processes"
2. Camila P. Salomon, Germano Lambert-Torres, Helga G. Martins, Claudio Ferreira, Claudio I. A. Costa. "Load flow computation via Particle Swarm Optimization"
3. Riccardo Poli. "Particle swarm optimization" ,Swarm Intelligence
4. I. O. Akwukwaegbu. "Voltage instability investigation of Nigeria 330kV power network using continuation method"
5. Sarika Sharma, Smarajit Ghosh. "FIS and hybrid ABC-PSO based optimal capacitor placement and sizing for radial distribution networks"
6. Camila Paes Salomon. "Hybrid Particle Swarm Optimization with Biased Mutation Applied to Load Flow Computation in Electrical Power Systems"
7. Muhammad Akram, Fariha Zafar. "Hybrid Soft Computing Models Applied to Graph Theory"
8. Pieter C. Allaart. "Prophet Regions for Discounted, Uniformly Bounded Random Variables"