Evaluating Objective Value Variance and Search Position Variance using Diverse Objective Functions in PSO

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***Abstract*—Engineers, economists, scientists, and managers constantly have to take numerous technicalandadministrative decisions at several times for the construction and maintenance of any system. Day by day the world becomes more and more multifaceted and competitive so the decision-making must be taken optimally. So optimization is the main actofattaining the paramount result under given circumstances.Optimization is referred to as a mathematical technique intended for finding maxima or minima of function in a certain practicable region. Every organization or industry is directly or indirectly involved in solving optimization problems. Several optimization techniques compete to provide the optimum solution. Particle Swarm Optimization (PSO) isa comparatively new, contemporary, and influential technique of optimization that has been empirically shown to accomplish well on many of these optimization problems. It is extensively used to identify the global optimum solution in a complex search space. The research paper aims at assisting the practitioners to improve results by implementing four different objective functions (@(x)(sum(x.^2,1)), @Himmelblau, @GoldsteinPrice, and @StyblinskiTang) via making a judicious selection of participating parameters. The research paper elaborated the adopted methodology via flowchart and appropriate algorithm. Four different cases, one for each objective function, have been implemented and the results have been obtained Objective Value Variance and Search Position Variance. The obtained results have been obtained over running multiple iterations and the consistent reduction in the value of participating parameters proves the worth of the conducted research.**

Keywords: Objective Function, Objective Value Variance, Optimization, PSO, Search Position Variance.

I. Introduction

Numerous real-life engineering design tasks necessitate the usage of numerical optimization techniques that can handle highly nonlinear multimodal problems, with numerous complex restraints on factors such as deflection, stress, geometric configuration, and load-carrying capability [1, 2]. Though some gradient-based deterministic algorithms have been presented during the past years, their clarification is a function of the initial search points and thus might not be the global optimum [3, 4].The primary aim of the optimization of the design is to minimize the cost of the production or to maximize the efficiency of the production [5, 6]. The optimization algorithm is an iterative technique for equating different results until the best or reasonable solution is accomplished. The main and prominent job in the formulation process is to determine the objective function in relevance with problem parameters and diverse design variables [7, 8]. The basic engineering objective is to perform the minimization of the overall cost of manufacturing or reduction of the overall weight of a module or maximization of the total life of a product or others [9].The majority of the objectives can be expressed mathematically, there are some which are not possible to formulate. To handle such scenarios, a mathematical expression is used [10]. Regardless of the availability of numerous optimization algorithms and techniques, none can be dignified to be the best for different cases [11, 12]. It has been observed that the technique which proved best to handle a certain type of problem may not perform that well in handling another type of problem [13, 14]. This is governed by several features like whether the function is differentiable and its concavity (convex or concave) [15, 16]. PSO algorithm is capable of solving complex mathematical problems existing in engineering. In the real world, the need may often arise to work on multiple objectives concurrently to enhance the overall performance of the system. Such multiple objective optimization algorithms are multifaceted and computationally exclusive [17, 18]. It is because of this that the most significant objective is selected as the objective function and the other objectives are encompassed as restraints by limiting their values within a convinced range [19,20]. The objective function can be classified into two categories to handle minimization problems or maximization problems [21]. In few algorithms, few minor structural changes would assist in performing minimization or maximization [22]. The duality principle permits the same algorithm to be used for minimization or maximization with a minor change in the objective function instead of a change in the entire algorithm [23, 24]. Suppose an algorithm is intended to solve a minimization problem, it can be comfortably converted to a maximization problem by multiplying the objective function by −1 and vice versa [25]. PSO has resembled evolutionary computation techniques such as GA (Genetic Algorithms). The search for finding the optimum solution is done by executing the number of iterations. The potential solutions known as particles or agents keep moving in the problem space following the existing optimum particles [26, 27].

II. Research Methodology

The ultimate goal of the research is to evaluate the objective value variance and search position variance using diverse objective functions. The detailed algorithm followed by the flowchart shown in Fig. 1 depicts the methodology adopted to conduct the research.

Algorithm

1. Firstly, initialize the participating parameters.
2. Examine weight on current search direction, global best, and local best followed by initializing the population count and the maximum number of generations.
3. Perform sampling of two random points in the search space for each particle and move initial points towards initial guess, by convex combination. *(Convex combination is a linear combination of points where all coefficients are non-negative and sum to 1).*
4. Set initial position and velocity of the population.
5. Check for a Warm start. If so, override the random initial point with the variable *x0. (Warm start denotes restarting the CPU without turning the power off. Program processing starts once again where Retentive data is retained. This warm-starting approach enables us to start training from a better initial point on the loss surface and often learn better models).*
6. Evaluate Function value at each particle in the population and Mark Best point, for each particle in the population.
7. Mark Value of best point, for each particle in the population and Mark Value of best point ever, overall points and allocate memory for the *dataLog.*
8. Compute a new generation of points and update each particle. Update current search direction, global direction, and local best direction.
9. Update position and clamp position to bounds and compute the best point.*(Clamp positioning refers to restricting the particle position within certain bounding).*
10. Record Log data, plot, and print and perform convergence and obtain results.
11. End.

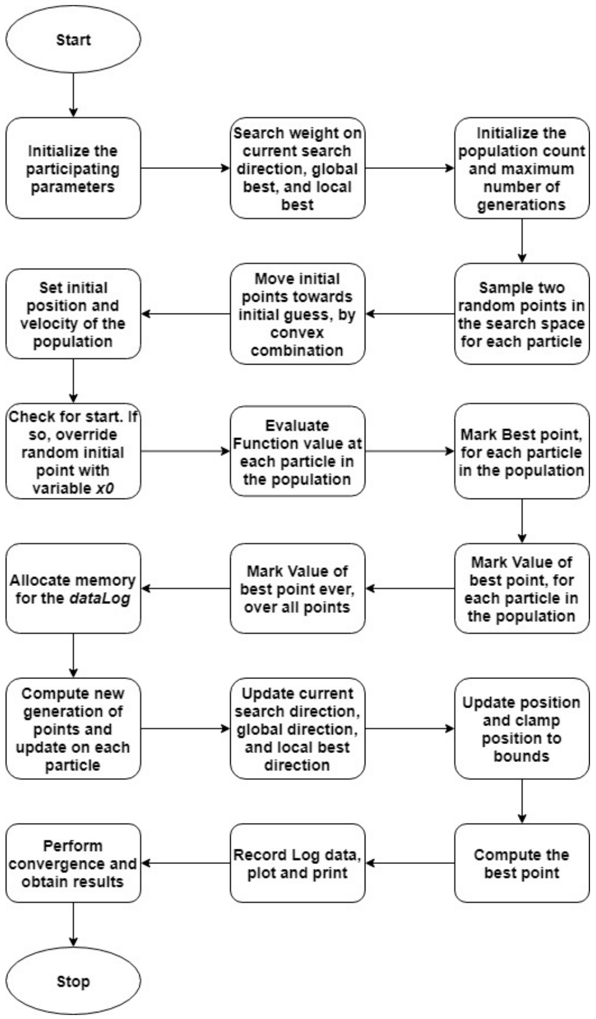

Fig.1: Flowchart Depicts the Adopted Research Methodology for Conducting the Research

III. Implementation and Results

This section elaborates the implemented research work via four diverse objective functions using four different cases. The considered parameters are listed and described below.

Considered Parameters

Object function –objFun
Lower bound on the search space – xLow
Upper bound on the search space – xUpp
Weight on current search direction – options.alpha
Weight on local best search direction – options.beta
Weight on global best search direction – options.gamma

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Size of Population – nPopulation
Maximum number of iterations – maxIter
Function to plot progress – plotFun

The value of the participating parameters has been altered to study the different cases. The obtained results have been depicted in both graphical and tabular forms for each case.

A. Case 1

Assigned Values -

objFun	-	@(x)(sum(x.^2,1))
xLow	-	ones(2,1)
xUpp	-	ones(2,1)
options.alpha	-	0.4
options.beta	-	0.9
options.gamma	-	0.9
nPopulation	-	10
maxIter	-	20
plotFun	-	@plotBowl

Fig. 2 shows the plotted graph using *@(x)(sum(x.^2,1))* as objective function and *@plotBowl* as plot function. After execution of 10 iterations, the evaluated objective value is 9.14e-06.

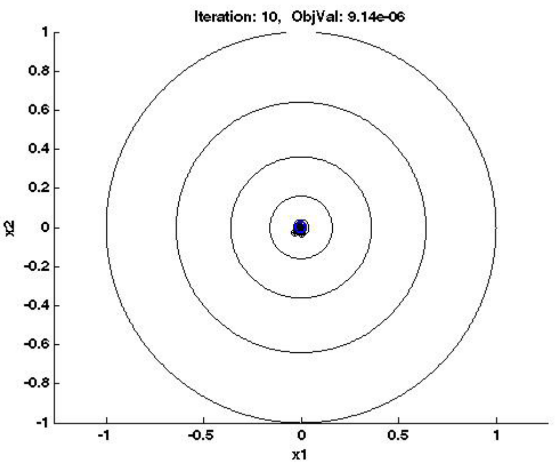

Fig. 2: The Evaluated Objective Value (*ObjVal*) after Execution of 10 Iterations

Figure 3 shows four segments. The X-axis in all four segments represents the number of iterations. Y-axis in the upper left segment denotes the objective value. The upper left segment shows the evaluated mean (*F_best*) in the blue-colored line, mean (*F*) in green colored line, and Global best in the red-colored line. In the upper right segment, the Y-axis represents the value of state for the two random points *x1* and *x2* in the search space. The blue-colored line denotes the plotted graphs for point *x1* and the green-colored lines for point *x2*. The lower left segment represents the calculated objective value variance. The Y-axis denotes objective variance. The var (*F_best*) is represented by a blue-colored line and the var (*F*) is represented by a green-colored line. The lower right segment deals with the evaluation of search position variance. The Y-axis represents the value of state for the two random points *x1* and *x2* in the search space. The blue-colored line denotes the plotted graphs for point *x1* and the green-colored lines for point *x2*. The downfall witnessed in the plotted lines of the graphs proves the worth of the conducted research

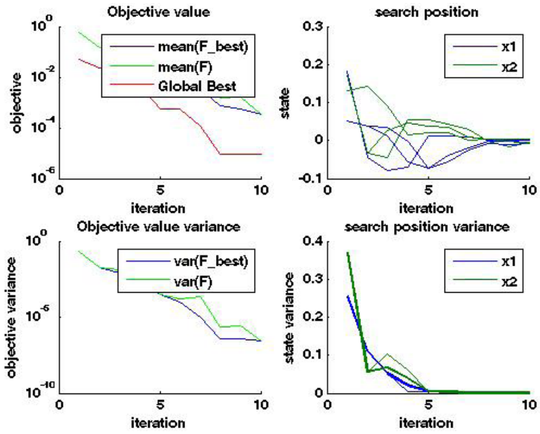

Fig. 3: Four Segments Depicting the Plotted Graphs for Objective Value, Search Position, Objective Value Variance, and Search Position Variance as per the Reading of Case 1

The obtained results as per Case 1 are mentioned in Table 1. The first column denotes the iteration number. *fBest* in the second column refers to the value of the best point for each particle.*fVar* in the third column refers to the objective value variance followed by *xVar* in the fourth column denoting the values for obtained representing search position variance. The reduction witnessed in the values of *fBest, fVar*, and *xVar* proves the worth of the conducted research.

Table 1: Table Illustrates the Evaluated Values for *fBest, fVar*, and *xVar*

Iteration	fBest	fVar	xVar
1	4.996e-02	2.066e-01	4.484e-01
2	2.230e-02	1.973e-02	1.245e-01
3	1.467e-02	1.240e-02	1.171e-01
4	5.018e-03	4.727e-03	6.172e-02
5	5.588e-04	3.074e-04	6.232e-03
6	5.588e-04	1.641e-04	9.260e-03
7	1.141e-04	2.155e-04	5.501e-03
8	9.139e-06	2.467e-06	1.233e-03
9	9.139e-06	2.918e-06	1.233e-03
10	9.139e-06	2.771e-07	2.362e-04

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Figure 4 represents the plotted graph as per the readings obtained in Table I. The graph for *fBest, fVar*, and *xVar* are denoted by blue-colored, orange-colored, and grey-colored lines.

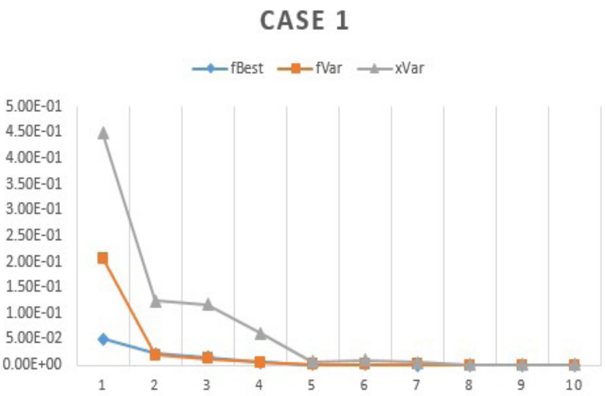

Fig. 4: Figure Represents the Plotted Graph as per the Readings Obtained in Table I

B. *Case 2*

Assigned Values

objFun	–	– @Himmelblau
xLow	–	-5*ones(2,1);
xUpp	–	– 5*ones(2,1)
options.alpha	–	– 0.4
options.beta	–	– 0.9
options.gamma	–	– 0.9
nPopulation	–	– 15
maxIter	–	– 50
plotFun	–	– @plotHimmelblau

Figure 5 shows the plotted graph using *@Himmelblau* as the objective function and *@plotHimmelblau* as the plot function. After the execution of 50 iterations, the evaluated objective value is 5.39e-08.

Figure 6 shows four segments. The X-axis in all four segments represents the number of iterations. Y-axis in the upper left segment denotes the objective value. The upper left segment shows the evaluated mean (*F_best*) in the blue-colored line, mean (*F*) in the green-colored line and Global best in the red-colored line. In the upper right segment, the Y-axis represents the value of state for the two random points *x1* and *x2* in the search space. The blue-colored line denotes the plotted graphs for point *x1* and the green-colored lines for point *x2*. The lower left segment represents the calculated objective value variance. The Y-axis denotes objective variance. The var (*F_best*) is represented by a blue-colored line and the var (*F*) is represented by a green-colored line. The lower right segment deals with the evaluation of search position variance. The Y-axis represents the value of state for the two random points *x1* and *x2* in the search space. The blue-colored line denotes the plotted graphs for point *x1* and the green-colored lines for point *x2*. The downfall witnessed in the plotted lines of the graphs proves the worth of the conducted research.

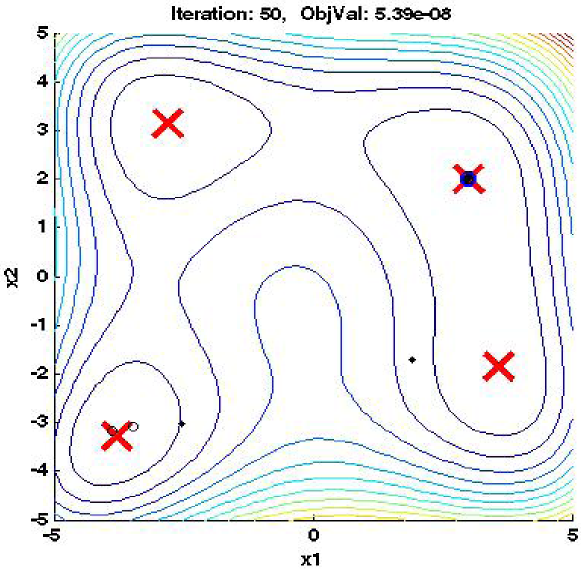

Fig.5: The Plotted Graph Using *@Himmelblau* as Objective Function and *@plotHimmelblau* as Plot Function as per Case 2

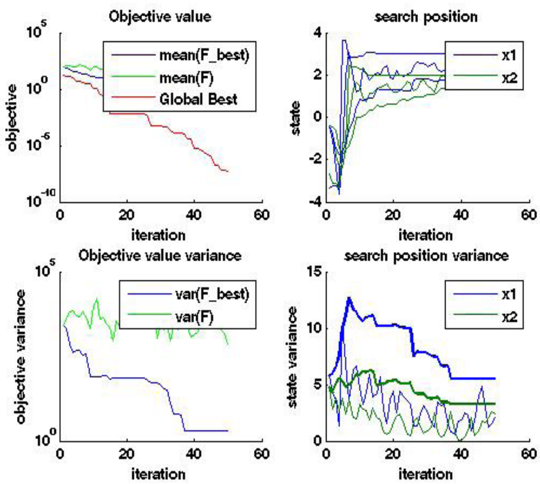

Fig.6: Four Segments Depicting the Plotted Graphs for Objective Value, Search Position, Objective Value Variance, and Search Position Variance as per the Reading of Case 2

The obtained results as per Case 2 are mentioned in Table II. The first column denotes the iteration number. *fBest*in the second column refers to the value of the best point for each particle. *fVar* in the third column refers to the objective value variance followed by *xVar* in the fourth column denoting the values for obtained representing

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search position variance.The reduction witnessed in the values of *fBest, fVar*, and *xVar* proves the worth of the conducted research.

Table 2: Table Illustrates the Evaluated Values for *fBest, fVar*, and *xVar*

Iteration	fBest	fVar	xVar
1	1.64E+01	2.57E+03	7.50E+00
2	1.42E+01	4.43E+03	5.03E+00
3	1.42E+01	6.35E+03	5.29E+00
4	1.04E+01	6.95E+03	3.02E+00
5	4.70E+00	5.21E+03	1.10E+01
6	4.70E+00	4.65E+03	7.25E+00
7	3.49E+00	6.57E+03	5.15E+00
8	2.77E+00	4.68E+03	6.64E+00
9	2.77E+00	2.13E+03	6.94E+00
10	1.14E+00	9.97E+03	5.74E+00
11	1.14E+00	1.55E+04	4.30E+00
12	3.47E-01	3.88E+03	5.13E+00
13	2.41E-01	4.35E+03	6.18E+00
14	2.41E-01	2.84E+03	4.88E+00
15	6.94E-03	2.33E+03	4.65E+00
CONTINUED			
35	1.29E-04	1.86E+03	3.24E+00
36	1.29E-04	3.19E+03	2.10E+00
37	1.14E-04	2.30E+03	2.76E+00
38	3.77E-05	2.21E+03	1.00E+00
39	3.77E-05	1.16E+03	1.77E+00
40	5.23E-06	1.38E+03	1.84E+00
41	5.23E-06	1.66E+03	2.54E+00
42	4.62E-06	2.60E+03	2.44E+00
43	1.95E-06	4.51E+03	2.27E+00
44	1.61E-06	3.02E+03	1.85E+00
45	8.65E-07	2.43E+03	4.12E+00
46	1.58E-07	6.38E+03	5.15E+00
47	1.58E-07	2.45E+03	3.33E+00
48	7.26E-08	1.92E+03	2.47E+00
49	7.26E-08	1.55E+03	2.96E+00
50	5.39E-08	6.88E+02	3.17E+00

Figure 7 represents the plotted graph as per the readings obtained in Table II. The graph for *fBest, fVar*, and *xVar* are denoted by blue-colored, orange-colored, and grey-colored lines.

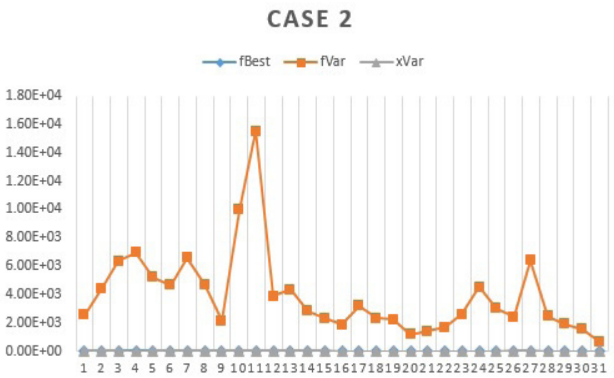

Fig.7: The Plotted Graph as per Case 2 Readings Obtained in Table II

C. Case 3

Assigned Values

objFun	–	@GoldsteinPrice
xLow	–	-2*ones(2,1);
xUpp	–	2*ones(2,1)
options.alpha	–	0.4
options.beta	–	0.9
options.gamma	–	0.9
nPopulation	–	15
maxIter	–	50
plotFun	–	@plotGoldsteinPrice

Figure 8 shows the plotted graph using @ *GoldsteinPrice* as the objective function and @ *plotGoldsteinPrice* as the plot function. After the execution of 46 iterations, the evaluated objective value is 4.88e-09. Although the number of iterations supposed to execute was fixed at 50 because the condition specified for converging Optimization (Exit: fVar < tolFun) did not hold beyond iteration 46, so it terminated.

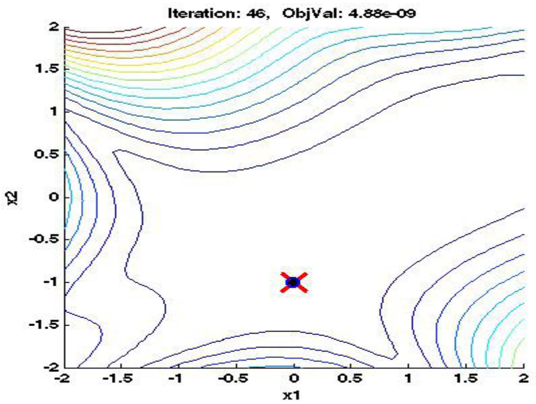

Fig. 8: The Plotted Graph Using @GoldsteinPrice as Objective Function and *@plotGoldsteinPrice* as plot Function as per Case 3

Figure 9 shows four segments. The X-axis in all four segments represents the number of iterations. Y-axis in the upper left segment denotes the objective value. The upper left segment shows the evaluated mean (*F_best*) in the blue-colored line, mean (*F*) in the green-colored line and Global best in the red-colored line. In the upper right segment, the Y-axis represents the value of state for the two random points *x1* and *x2* in the search space. The blue-colored line denotes the plotted graphs for point *x1* and the green-colored lines for point *x2*. The lower left segment represents the calculated objective value variance. The Y-axis denotes objective variance. The var (*F_best*) is represented by a blue-colored line and the var (*F*) is represented by a green-colored line. The lower right segment deals with the evaluation of search position variance. The Y-axis represents the value of state for the two random points *x1* and *x2* in the search space. The blue-colored line denotes the plotted graphs for point *x1* and the green-colored lines for point *x2*. The downfall witnessed in the plotted lines of the graphs proves the worth of the conducted research.

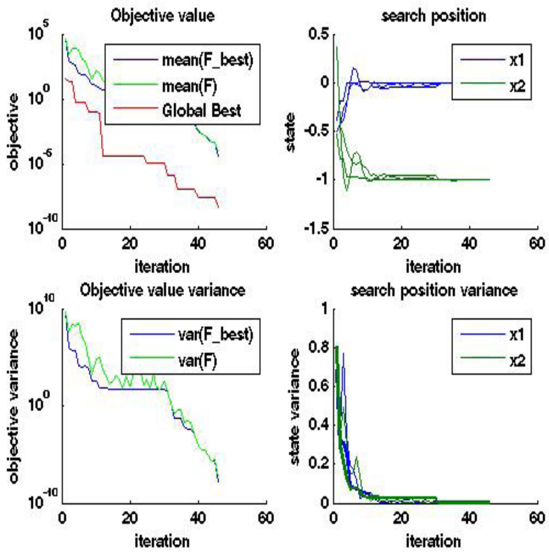

Fig. 9: Denotes Four Segments Depicting the Plotted Graphs for Objective Value, Search Position, Objective Value Variance, and Search Position Variance as per the Reading of Case 3

The obtained results as per Case 3 are mentioned in Table III. The first column denotes the iteration number. *fBest*in the second column refers to the value of the best point for each particle. *fVar* in the third column refers to the objective value variance followed by *xVar* in the fourth column denoting the values for obtained representing search position variance. The reduction witnessed in the values of *fBest, fVar*, and *xVar* proves the worth of the conducted research.

Table 3: Table Illustrates the Evaluated Values for *fBest, fVar*, and *xVar*

Iteration	fBest	fVar	xVar
1	3.91E+01	4.63E+09	1.06E+00
2	2.05E+01	4.39E+07	5.28E-01
3	2.05E+01	2.10E+08	9.15E-01
4	5.66E-01	1.61E+08	4.60E-01
5	5.66E-01	2.89E+08	2.43E-01
6	5.66E-01	1.08E+07	2.33E-01
7	5.66E-01	3.20E+06	2.66E-01
8	1.07E-01	6.54E+04	1.39E-01
9	1.07E-01	1.80E+03	4.93E-02
10	1.07E-01	7.15E+04	6.23E-02
11	7.24E-02	1.03E+05	5.79E-02
12	4.15E-05	4.72E+03	3.49E-02
13	4.15E-05	1.24E+03	2.51E-02
14	4.15E-05	1.83E+02	1.37E-02
15	4.15E-05	3.35E+02	1.25E-02
CONTINUED			
31	1.31E-06	2.63E+01	2.99E-03
32	1.31E-06	1.80E+00	1.15E-03
33	1.31E-06	1.55E-01	3.69E-04
34	1.06E-07	3.29E-01	2.71E-04
35	1.06E-07	3.49E-01	2.06E-04
36	1.06E-07	1.99E-02	1.04E-04
37	1.06E-07	2.46E-02	1.02E-04
38	1.06E-07	1.72E-02	7.42E-05
39	1.06E-07	1.54E-03	2.23E-05
40	2.32E-08	8.85E-05	8.18E-06
41	2.32E-08	2.84E-05	5.79E-06
42	2.32E-08	2.65E-05	2.64E-06
43	2.32E-08	8.24E-06	2.03E-06
44	2.32E-08	2.33E-06	1.78E-06
45	2.32E-08	2.64E-06	1.40E-06
46	4.88E-09	6.69E-08	2.38E-07

Figure 10 represents the plotted graph as per the readings obtained in Table III. The graph for *fBest, fVar*, and *xVar* are denoted by blue-colored, orange-colored, and grey-colored lines.

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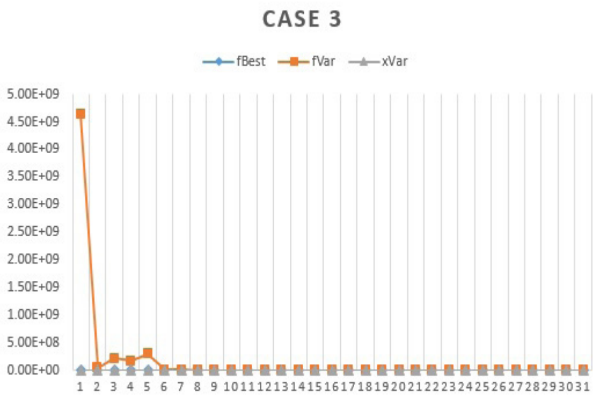

Fig. 10: The Plotted Graph as per the Readings of Case 3 Obtained in Table III

D. Case 4

Assigned Values

objFun	– @StyblinskiTang
xLow	– -5*ones(2,1);
xUpp	– 5*ones(2,1)
options.alpha	– 0.5
options.beta	– 1.1
options.gamma	– 1.1
nPopulation	– 20
maxIter	– 50
plotFun	– @plotStyblinskiTang

Figure 11 shows the plotted graph using *@StyblinskiTang* as the objective function and *@plotStyblinskiTang* as the plot function. After the execution of 24 iterations, the evaluated objective value is -78.3. Although the number of iterations supposed to execute was fixed at 50 because the condition specified for converging Optimization (Exit: fVar < tolFun) did not hold beyond iteration 24, so it terminated.

Figure 12 shows four segments. The X-axis in all four segments represents the number of iterations. Y-axis in the upper left segment denotes the objective value. The upper left segment shows the evaluated mean (*F_best*) in the blue-colored line, mean (*F*) in the green-colored line and Global best in the red-colored line. In the upper right segment, the Y-axis represents the value of state for the two random points *x1* and *x2* in the search space. The blue-colored line denotes the plotted graphs for point *x1* and the green-colored lines for point *x2*. The lower left segment represents the calculated objective value variance. The Y-axis denotes objective variance. The var (*F_best*) is represented by a blue-colored line and the var (*F*) is represented by a green-colored line. The lower right segment deals with the evaluation of search position variance. The Y-axis represents the value of state for the two random points *x1* and *x2* in the search space. The blue-colored line denotes the plotted graphs for point *x1* and the green-colored lines for point *x2*. The downfall witnessed in the plotted lines of the graphs proves the worth of the conducted research.

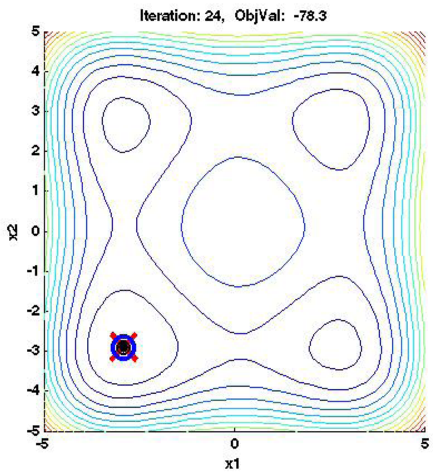

Fig.11: The Plotted Graph using *@StyblinskiTang* as Objective Function and *@plotStyblinskiTang* as Plot Function as per Case 3

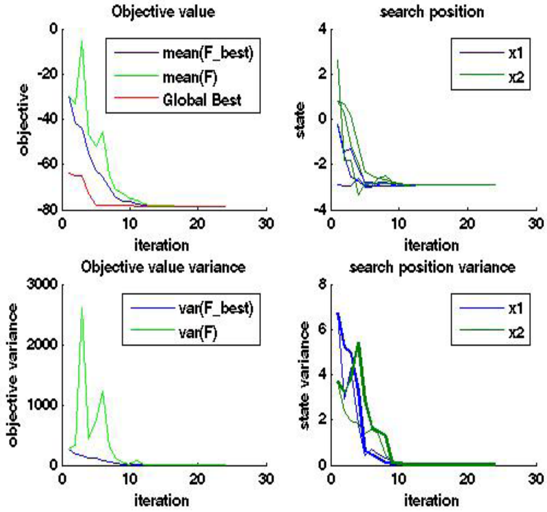

Fig.12: Four Segments Depicting the Plotted Graphs for Objective Value, Search Position, Objective Value Variance, and Search Position Variance as per the Reading of Case 4

The obtained results as per Case 4 are mentioned in Table IV. The first column denotes the iteration number. *fBest*in the second column refers to the value of the best point for each particle. *fVar* in the third column refers to the objective value variance followed by *xVar* in the fourth column denoting the values for obtained representing search position variance. The reduction witnessed in the values of *fBest, fVar*, and *xVar* proves the worth of the conducted research.

TABLE 4: TABLE ILLUSTRATES THE EVALUATED VALUES FOR *FBEST, FVAR*, AND *XVAR*

Iteration	fBest	fVar	xVar
1	-6.39E+01	2.71E+02	7.67E+00
2	-6.50E+01	3.25E+02	3.81E+00
3	-6.50E+01	2.62E+03	4.69E+00
4	-7.30E+01	4.34E+02	2.58E+00
5	-7.83E+01	7.66E+02	1.48E+00
6	-7.83E+01	1.22E+03	1.73E+00
7	-7.83E+01	3.06E+02	1.49E+00
8	-7.83E+01	1.25E+02	5.36E-01
9	-7.83E+01	4.15E+01	2.56E-01
10	-7.83E+01	1.32E+01	1.22E-01
11	-7.83E+01	6.42E+01	8.70E-02
12	-7.83E+01	1.50E+00	4.08E-02
13	-7.83E+01	9.85E-01	2.57E-02
14	-7.83E+01	1.08E-01	1.03E-02
15	-7.83E+01	4.55E-02	5.93E-03
16	-7.83E+01	4.57E-02	5.13E-03
17	-7.83E+01	6.23E-04	7.01E-04
18	-7.83E+01	1.67E-03	1.18E-03
19	-7.83E+01	6.81E-04	5.63E-04
20	-7.83E+01	9.01E-05	2.52E-04
21	-7.83E+01	4.03E-04	3.53E-04
22	-7.83E+01	3.76E-06	4.38E-05
23	-7.83E+01	2.23E-05	9.33E-05
24	-7.83E+01	2.62E-07	1.76E-05

Figure 13 represents the plotted graph as per the readings obtained in Table IV. The graph for *fBest, fVar*, and *xVar* are denoted by blue-colored, orange-colored, and grey-colored lines.

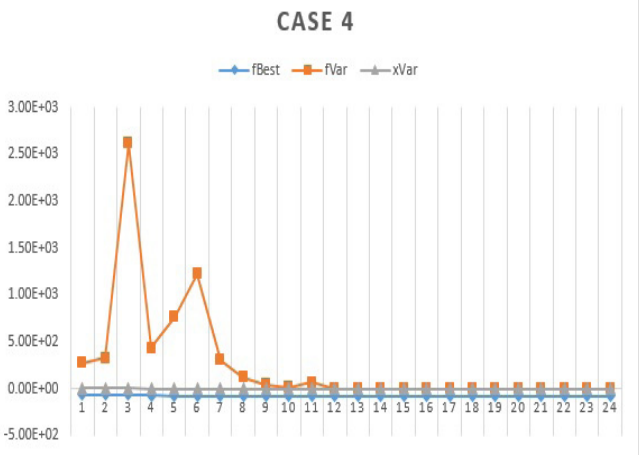

Fig.13: The plotted graph as per the readings obtained in Table IV

IV. CONCLUSION

The implementation of four different objective functions has been conducted in the research paper. The performance of each objective function is elaborated via obtaining readings for *fBest, fVar,* and *xVar*in tabular format over multiple iterations. The performance of objective functions in each case has been simulated using MATLAB and the obtained results have been graphically illustrated. The readings of participating parameters have witnessed a consistent reduction in their values and the plotted lines in the graphs show continuous downwards movement. The plotted graphs justify that the research methodology adopted for the implementation of four objective functions understudy has proved to be effective. The objective function can be selected as per the requirements of the application, scenario, and value of participating parameters. In the future, a more objective function can be implemented using the proposed methodology in the research paper with a greater number of iterations and populations.

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