PalArch's Journal of Archaeology of Egypt / Egyptology

MANY OBJECTIVE OPTIMIZATION PROBLEM USING BAT ALGORITHM BASED ON INVERTED GENERATIONAL INDICATOR

Maryam Raad[1], Iraq T. Abass[1]

[1]University of Baghdad College of Science Department of Mathematics.

Maryam Raad , Iraq T. Abass , Many Objective Optimization Problem Using Bat Algorithm Based On Inverted Generational Indicator , Palarch's Journal Of Archaeology Of Egypt/Egyptology 18(7). ISSN 1567-214x.

Keyword: Many Objective Problems, Bat Algorithm, InvertedGenerational Distance.

Abstract

The problems around us are becoming more complex at the same time and at the same time our mother nature is guiding us to solve these natural problems. Nature offers us some logical and effective ways to find a solution to these problems.

Although computational strategies for taking care of Many-objective Optimization Problems (MOPs/I) have been accessible for a long time, the ongoing utilization of Evolutionary Algorithm (EAs) to such issues gives a vehicle which to tackle extremely enormous scope MOPs/I.

MOBAT/I is a many-objective bat algorithm that incorporates the dominance concept with the decomposition approach is proposed. Whilst decomposition simplifies the multi-objective problem (MOP) by rewriting it as a set of Tchebycheff Approach, solving these problems simultaneously, within the BAT framework, might lead to premature convergence because of the leader selection process which uses the Tchebycheff Approach as a criterion. Dominance plays a major role in building the leaders archive allowing the selected leaders to cover less dense regions avoiding local optima and resulting in a more diverse approximated Pareto front. Results from 35 standard MOPs show MOBAT/I it outperforms some developmental methods based on decomposition. All the results were done by MATLAB (R2017b).

1- Introduction

This chapter introduces the present research. It takes into consideration the background of the study; state the research objectives, research question, significance of the study, scope and limitations of the study and layout the organization of the paper.

In multi-objective optimization, usually there is no single optimal solution but rather a set of Pareto optimal solutions. Naturally, density estimation plays a fundamental role in the evolutionary process of multi-objective optimization for an algorithm to obtain a representative and diverse approximation of the Pareto front [1, 2].

Multi-objective Bat Algorithm (MOBAT) is proposed to find the Pareto optimal set for Multi-Objective (MO) functions by varying weights [3]. Also in [4] the author present extended BAT to solve multi-objective problems and formulate a Multi-Objective Bat Algorithm (MOBAT). We will first validate it against a subset of many-objective test functions. Then, we will apply it to solve design optimization problems in engineering, such as bi-objective beam design. In the work of the paper [5] the author contemplated on the multi-objective BAT algorithm (MOBAT) a biological inspired meta-heuristic and have successfully applied to solve the problem floor planning in VSLI design. A Multi-Objective Optimization Problem (MOOP) is proposed in [6] to achieve the both mentioned objectives. For this purpose, a new simple optimization algorithm known as Bat Algorithm (BAT) based on Weight Sum Method (WSM) has been used to resolve the MOOP. Therefore from the literature we can say here no study before combining between MOBAT and Inverted Generational Distance.

Moreover, in another study, a comparison of algorithms for training feed forward neural networks is done. Two gradient descent algorithms (Backpropagation and Levenberg Marquardt), and three population-based heuristic: Bat algorithm, Genetic algorithm, and Particle Swarm optimization algorithm are used for testing. Bat algorithm outperforms all other algorithms in training feed forward neural networks [7]. These studies encourage using BAT in further experiments and in further real-world applications. The benefit of the using bat algorithm is to obtain solutions based on population and local search based algorithms. This combination gives us global diversity as well as local rigorous exploitation, which is important for metaheuristic algorithms. So, Bat algorithm is the combination of PSO and local search, which further uses pulse rate control and loudness [8]. By adapting the approach of reference sets, the MOBAT are used for the MaOPs and provide a good balance in diversity and convergence which is the main issue in the MaOPs. The main purpose of the paper is to improve the many-objective algorithm result, by implementing a new bat-inspired algorithm for many-objective optimization problems by using reference set approach to get good convergence and diversity. In this paper, we introduce a new algorithm based on inverted generational distance algorithm to minimize computational efforts of the field of many objective problems.

2- Definition and Basic Concept

The present study aims to solve the following types of problems (without loss of generality, the present study will assuming only minimization problems):

$$\text{Minimize} \quad f_i\,(x) = [f_1(x), f_2(x), \dots, f_k(x)]. \qquad (1.1)$$

Subject to:

$$g_i(x) \leq 0\,, i = 1, \dots, m; \qquad (1.2)$$

$$h_j(x) = 0\,, j = 1, \dots, p; \qquad (1.3)$$

Where$x = [x_1 : x_2, \dots, x_n]^T$is the vector of decision variables $f_i : R^n \to R;\ i = 1, \dots, k$ are the objective functions and $g_i;\ h_j : R^n$ to R, $i = 1, .., m,$ and $j = 1, \dots,$ p are the constraint functions of the problem? To describe the objective concept of optimality, the researcher introduces the following definitions:

Definition 1[9]: (Multi-objective Optimization Problem (MOP)). A MOP includes a set of n parameters (decision variables), a set of m objective functions, and a set of k constraints. Objective functions and constraints are functions of the decision variables. The optimization goal is to

$$\text{Minimize } y = f(x) = (f_1(x);\ f_2(x);\ \ldots;\ f_m(x))$$
$$\text{subj.: to } e(x) = (e_1(x);\ e_2(x);\ \ldots;\ e_k(x)) \leq 0$$

where$x = (x_1, x_2, \ldots, x_n) \in X$ and $y = (y_1, y_2, \ldots, y_m) \in Y$ and x is called the decision vector, y is the objective vector, X is denoted as the decision space and Y is called the objective space. The constraints $e(x) \leq 0$ determine the set of feasible solutions.

Definition 2[9]: (Pareto-dominance).
For any two decision vectors a and b,

$a > b$ (a dominates b) iff $f(a) < f(b)$

$a > b$ (a weakly dominates b) iff $f(a) \leq f(b)$

$a \sim b$ (a is indifferent to b) iff $f(a) \ngeq f(b) \wedge f(b) \ngeq f(a)$

In this definition, the relations =, ≤ and < on objective vectors are defined as follows:

Definition3[9]: (Pareto-optimality)
A decision vector $x \in X_f$is said to be non-dominated regarding a set $A \subseteq X_f$iff

$$\nexists a \in A : a > x$$

If it is clear from the context which set A is meant, is will be simply omitted in the following. Moreover, x is said to be Pareto optimal iff x is non-dominated regarding X_f .
The entirety of all Pareto-optimal points is called the Pareto-optimal set; the corresponding objective vectors form the Pareto-optimal front or surface.

Definition4[9]: (Pareto frontier)

For a given system, the Pareto frontier or Pareto set is the set of parameterizations (allocations) that are all Pareto efficient. Finding Pareto frontiers is particularly useful in engineering. By yielding all of the potentially optimal solutions, a designer can make focused tradeoffs within this constrained set of parameters, rather than needing to consider the full ranges of parameters [9].

The Pareto frontier, P(Y), may be more formally described as follows. Consider a system with function $f : Rn \rightarrow Rm$, where X is a compact set of feasible decisions in the metric space R^n , and Y is the feasible set of criterion vectors in R^m , such that $Y = \{y \in Rm : y = f(x), x \in X\}$.

we assume that the preferred directions of criteria values are known. A point $'' \in R^m$ is preferred to (strictly dominate) another point $y' \in R^m$, written as $y'' > y'$ .The Pareto frontier is thus written as:

$P(Y) = \{y' \in Y : \{y'' \in Y : y'' > y', y' \neq y''\} = \emptyset\}$.

Definition 5[9]: Given two vectors, namely$x_1, x_2 \in R^n, x_1 \leq x_2$ if $x_{i_1} \leq x_{i_2}, i = 1, 2 \ldots, k$, and x_1 dominates x_2 (denoted by $x_1 < x_2$) if $x_1 < x_2$and $x_1 \neq x_2$.

Definition 6 [9]:A vector of decision variables $x_1 \in X \subset R^n$ is non-dominated with respect to X, if no $x_2 \in X$ exists, such that $f(x_2) < f(x_1)$.

Definition 7 [9]: A vector of decision factors $x^* \in F \subset R^n$(F is the feasible region) is Pareto optimal if it is non-dominated with respect to F.

Definition 8 [9]: The Pareto optimal set P^* is defined as follows: $P^* = \{x_1 \epsilon F : x_1$ is Pareto optimal$\}$.

Definition 9 [9]: The Pareto front (PF^*) is defined by the following:
$PF^* = \{f(x_1) \epsilon R^k : x_1 \epsilon P^*\}$.

3- The Proposed Method

In this section, we first present a few definitions utilized in MOPs a while. At that point, we present the system of the proposed calculation. Next, we depict the wellness task process. At last, the procedures for mating and natural choice procedures are introduced .
Bats are are mammals with wings and echolocation capacity. Around 996 distinctive bat species have been distinguished around the world, and they represent about 20% of all well evolved creature species [28]. Based on swarm insight and bat perception there are another improvement calculation to solve the mentioned problem known as BAT[10]. One can reenact the pieces of the echolocation qualities of smaller scale bat by utilizing the BAT. The upsides of this calculation incorporate effortlessness, adaptability, and simple execution. Moreover, the calculation proficiently takes care of a wide scope of issues, for example, exceptionally nonlinear issues. BAT additionally gives promising ideal arrangements rapidly and functions admirably with confounded issues. Inconveniences of this calculation are as per the following: combination happens rapidly at beginning times and the intermingling rate diminishes. Moreover, no scientific examination connects the parameters with intermingling rates. To acquire better ideal method for multi-target capacities utilizing BAT, the specialist builds up a calculation called MOBA by presenting two new segments which are file and pioneer as found in the MOPSO calculation proposed by [11]. The chronicle is answerable for sparing and reestablishing the most noteworthy non-overwhelmed and no controllable Pareto ideal arrangements that have been gotten to date. The chronicle likewise shows a primary unit, which is the control unit of the file. This unit controls the quantity of no controlling arrangements when new no controlling arrangements exist.
In MaBAT/IGD calculation, the most reasonable arrangement acquired is utilized. This pioneer guides individuals inside the exploration zone to acquire an answer near the most appropriate arrangement. Be that as it may, arrangements can't be in a many objective inquire about space contrasted and Pareto's optimal ideas. The pioneer choice component is intended to deal with the issue. A chronicle contains the most reasonable non-prevailing arrangements got. The pioneer chooses the segment from the jam-packed fragments of the space arrangement and offers one of the non-prevailing arrangements. Determination is performed through the roulette wheel with the accompanying opportunities for each hyper:

MaBAT/IGD Procedure with Inverter Indicator

Set $k := 0$ and velocity =0 μ=0.1, $r0 = 0.5, A = 0.6$.
Randomly initialize Point P_i for n. population ;
Calculate the fitness values of initial Population: f (P);
Find the non-dominated solutions and initialized the archive with them
WHILE (the termination conditions are not met)
1) BAT Steps
$Q = Qmin + (Qmin - Qmax) * rand$ (equation 1)
$P_{leader1} = \text{Select Leader (archive)}$
$V_{(t+1)} = V_{(t)} + \left(P_{leader1} - P_{(t)}\right) * Q$ (equation 2)
$P_{new} = P_{(t)} + V_{(t+1)}$(equation 3)
If rand > r
$P_{leader2} = \text{Select Leader(archive)}$
$P_{new}=P_{(t)}+rand * \left(P_{leader2} - P_{(t)}\right)$
End
if P_{new} dominated on $P_{(t)}\& (rand < A)$
$P_{(t)}=P_{new}$
End
If rand$<(\frac{\mathbf{1-(k-1)}}{\mathbf{Max\ iteration-1}})^{\mathbf{1/\mu}}$
$S = \text{Mutation}(P_{(t)})$
if P_{new} dominated on $P_{(t)}\&(\text{rand} < A)$
$P_{(t)}=S$
End
End
Find the non-dominated solutions
Update the archive with respect to the obtained non-dominated solutions
Ifthe archive is full
Run the grid mechanism to omit one of the current archive members
Add the new solution to the archive
end if
If any of the new added solutions to the archive is located outside the hyper cubes
Update the **grids to** cover the new solution(s)
end if
Inc
rease r and reduce A
Set $k := k + 1;$
END WHILE

4- Experimental and Results

To investigate the effectiveness of our proposed MaBAT/IGD, especially on problems with irregular PF shapes, a total of 18 test problems with different PF shapes are selected fromthe DTLZ[12] and UF [13].

In this article, the well-known HV [14] and inverted generational distance (IGD) [15] are used as the performance indicators. Both HV and IGD are able to reflect the convergence and diversity of the final solution set produced by the algorithms. A larger HV value or a smaller

IGD value indicates a better approximation to the true PF. When computing HV, a reference point dominated by the nadir point of the true PF is carefully specified for various problems.

4.1.1 Inverted Generational Distance(IGD)

Let Sbe a result solution set of an MOEA on a given MOP. Let R be a set of uniformly distributed representative points of the PF. The IGD value of S relative to R can be calculated as [1].

$$IGD(S,R) = \frac{\sum_{r\in R} d(r,S)}{|R|}$$

Where d(r, S) is the minimum Euclidean distance between r and the points in S, and |R| is the cardinality of R. Note that, the points in R should be well distributed and |R| should be large enough to ensure that the points in R could represent the PF very well. This guarantees that the IGD value of S is able to measure the convergence and diversity of the solution set. Thelower the IGD value of S, the better its quality [16].
To calculate the IGD value of a result set S of an MOEA running on an MOP, a set R of representative points of the PF needs to be given in advance.

4.1.2 Hyper volume Indicator

The hyper volume indicator $I_{\text{hyp}}(\mathcal{A})$, computes the volume of the region, H, delimited by a given set of points, A, and a set of reference points, N.

$$I_{\text{hyp}}(\mathcal{A}) = \text{volume}\left(\bigcup_{\forall a\in\mathcal{A};\forall n\in\mathcal{N}} \text{hypercube}(\mathrm{a},\mathrm{n})\right)$$

Therefore, larger values of the indicator will correspond to better solutions.
The hyper volume indicator is also known as the S metric or the Lebesgue measure. It has many attractive features that had favored its application and popularity. In particular, it is the only indicator that has the properties of a metric and the only to be strictly Pareto monotonic [16]. Because of these properties this indicator has been used not only for performance assessment but also as part of some evolutionary algorithms.

5- Procedure for Analysis

Centred on the mean, standard deviation (SD), MaBAT/IGD point and Wilcoxon marked location test measurements of the ability figures; the test results will be shown.

(a) Mean (x) shall be processed as the number of the multitude of noticed results from the example isolated by the all-out number of these results.

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

(b) SD is a measure that evaluates the variety or scattering of a bunch of information for the capacity esteems.

$$SD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2}$$

(c) Wilcoxon marked position test the Wilcoxon marked position test measurement decides the distinction between two examples [17] and gives an elective trial of area that is influenced by the sizes and indications of these distinctions. This test answers the accompanying theories:

H0: mean (A) - mean (B)
H1: mean (A) - mean (B),

Where the results of the first and second equations are signified by A and B, respectively. Additionally, this measure tests whether one estimate beats the other. Let di mean the difference in taking care of ith out of n problems between the presentation scores of two calculations. Enable R^+ to mean the number of positions for the problems in which the second is beaten by the key calculation. Ultimately, let R− address the amount of positions for the problems with which the following estimate defeats the first. The positions of several 0 are evenly split between the entireties. On the off chance that these totals have an odd number, at that point one of them is ignored.

$$R^+ = \sum_{d_i>0} rank(d_i) + \frac{1}{2}\sum_{d_i=0} rank(d_i)$$

$$R^- = \sum_{d_i<0} rank(d_i) + \frac{1}{2}\sum_{d_i=0} rank(d_i)$$

In order to contrast the equations at an immense degree of alpha = 0.05, we use MATLAB to find p esteem. Where the p-esteem is not precisely the essential stage, the invalid hypothesis is denied. R+ addresses a high mean estimate that illustrates predominance over multiple calculations through diverse test arrangements. Across all experiments, this algorithm beats all algorithms. While $\left(R^+ = \frac{n\times(n+1)}{2}\right)$ this algorithm outperforms all algorithms across all Exploration.

6- Results And Discussion

This segment is committed to the presentation confirmation of the proposed calculation. The proposed many-objective bat calculation (MaBAT/IGD) with decay is actualized in Matlab, and registering time is inside a couple of moments to not exactly a moment, contingent upon the issue of intrigue. We have tried it utilizing an alternate scope of parameters, for example, populace size (n), din decrease, and heartbeat decrease rate β .

The trial results have confirmed the adequacy of the proposed methodology in adjusting closeness and assorted variety. Then again, scientists have likewise structured a scope of decay based calculations particularly for multi-objective streamlining. To know how serious MaBAT/IGD were, we contrast it and two multi-objective PSO calculations that are illustrative of the best in class. These two calculations are MOPSO [11], MOEA/D [10]. Every calculation is run multiple times to accomplish metric (IGD) and (HV) for each test work. The mean qualities and standard deviation of the outcomes are gathered in Tables 1. The subsequent non-commanded fronts are plotted in Figures (1) and(2).

Table 1: Comparative between algorithms by using Inverted Generational distance when (M=2,3and 5)

Problems	N	M	D	MOEAD	MOPSO	NSGAIII	SPEA2	MaBAT/IGD
DTLZ1	100	2	30	2.9630e-1 (1.34e-1) -	5.5641e-1 (1.13e-1) -	1.0992e-1 (2.81e-2) -	1.1190e-1 (3.42e-2) -	4.1514e-2 (1.31e-2)
DTLZ2	100	2	30	1.4872e-1 (6.26e-2) -	1.1283e-1 (1.49e-2) -	3.6581e-2 (8.66e-3) -	4.1050e-2 (1.60e-2) -	1.3897e-2 (1.05e-3)
DTLZ3	100	2	30	3.1616e-1 (3.08e-2) -	5.5253e-1 (2.42e-2) -	2.2442e-1 (5.47e-2) -	1.8894e-1 (4.50e-2) -	1.1658e-1 (4.93e-2)
DTLZ4	100	2	30	7.1005e-2 (3.98e-3) -	1.0216e-1 (1.25e-2) -	4.6273e-2 (1.25e-3) -	4.4958e-2 (1.51e-3) -	4.1961e-2 (1.42e-3)
DTLZ5	100	2	30	5.1167e-1 (9.70e-2) -	3.3860e+0 (2.58e-1) -	2.6546e-1 (6.24e-2) =	2.7261e-1 (4.92e-2) =	3.3259e-1 (1.38e-1)
+/-/=				0/5/0	0/5/0	0/4/1	0/4/1	

Table 2: Comparative between algorithms by using hyper volume when (M=2,3 and 5)

Problems	N	M	D	MOEAD	MOPSO	NSGAIII	SPEA2	MaBAT/IGD
DTLZ1	100	2	30	4.5912e-1 (6.89e-2) -	1.4496e-1 (7.39e-2) -	5.9015e-1 (3.44e-2) -	5.9391e-1 (2.92e-2) -	6.6163e-1 (2.28e-2)
DTLZ2	100	2	30	6.2558e-1 (3.05e-2) -	5.9123e-1 (1.31e-2) -	6.7905e-1 (7.25e-3) -	6.8058e-1 (9.00e-3) -	7.0530e-1 (8.52e-4)
DTLZ3	100	2	30	3.8347e-1 (3.98e-2) -	1.3245e-1 (1.51e-2) -	4.5941e-1 (5.13e-2) -	4.8875e-1 (4.38e-2) -	5.9191e-1 (3.64e-2)
DTLZ4	100	2	30	3.4011e-1 (4.95e-3) -	3.0399e-1 (1.42e-2) -	3.8326e-1 (1.39e-3) -	3.8610e-1 (1.32e-3) =	3.8674e-1 (1.93e-3)
DTLZ5	100	2	30	1.4456e-1 (6.89e-2) -	0.0000e+0 (0.00e+0) -	2.4549e-1 (5.85e-2) =	2.3062e-1 (6.29e-2) =	2.3325e-1 (8.92e-2)
+/-/=				0/5/0	0/5/0	0/4/1	0/3/2	

Table 3: Comparative between algorithms by using Inverted Generational distance when (M=2,3 and 5)

Problem	M	D	MOEAD	NSGAII	MPSOD	SPEA2	MaBAT/IGD

s							
DTLZ6	2	30	4.4612e-1 (1.75e-1) -	2.5343e-1 (1.27e-1) =	8.6609e-1 (1.62e-1) -	1.6756e-1 (8.20e-2) =	2.2034e-1 (1.34e-1)
DTLZ7	2	30	4.8035e-1 (1.25e-1) -	1.6598e-1 (1.47e-1) -	1.3178e-1 (4.85e-2) -	1.4251e-1 (1.39e-1) -	2.5947e-2 (4.69e-2)
DTLZ8	3	30	3.9233e-1 (2.49e-1) -	2.7874e-1 (7.04e-2) -	4.9067e-1 (3.89e-2) -	2.4018e-1 (7.61e-2) -	1.5082e-1 (7.46e-2)
DTLZ9	3	30	3.3067e-1 (3.45e-2) -	3.4058e-1 (1.11e-1) -	6.0632e-1 (3.60e-2) -	2.8540e-1 (9.38e-2) -	1.6868e-1 (8.89e-2)
+/-/=			1/3/0	1/2/1	0/4/0	1/3/1	

7- Convergence Graphs

Convergence graphs have been made for the datasets that represent how fast the fitness value reaches convergence with the number of iterations. 100000 iterations have been run for all datasets. These graphs show the efficiency of our proposed algorithm to reach the best value faster. MOEA/D, MOPSO, NSGAII, and SPEA2 algorithms have been compared for this result. 100000 iterations of Hyper Volume (HV)and (IGD) have been run on all five algorithms and their convergence graphs have been plotted.

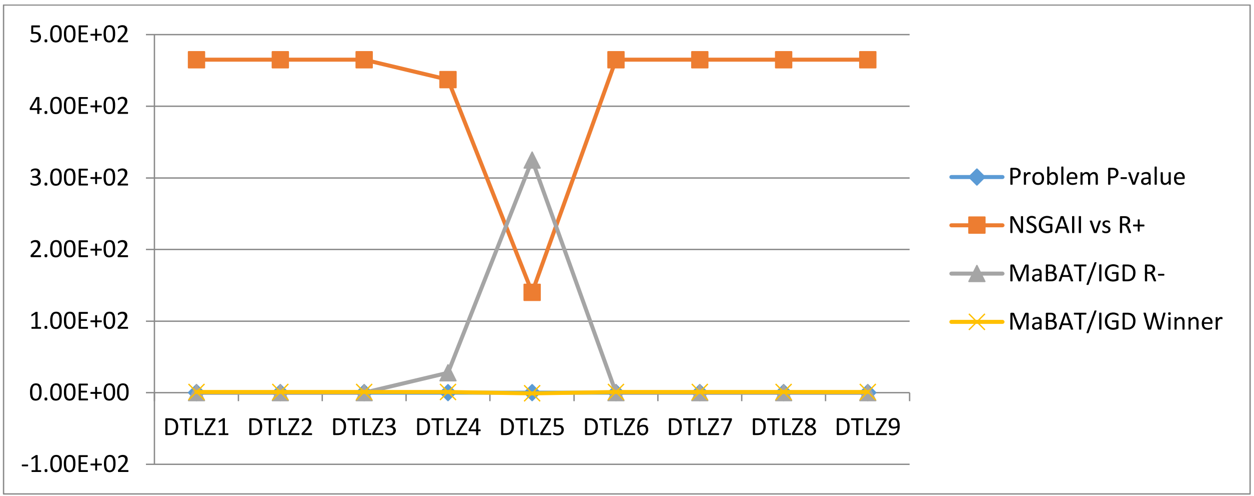

Figure 1: Number of functions VS Fitness Value Graph for IGD

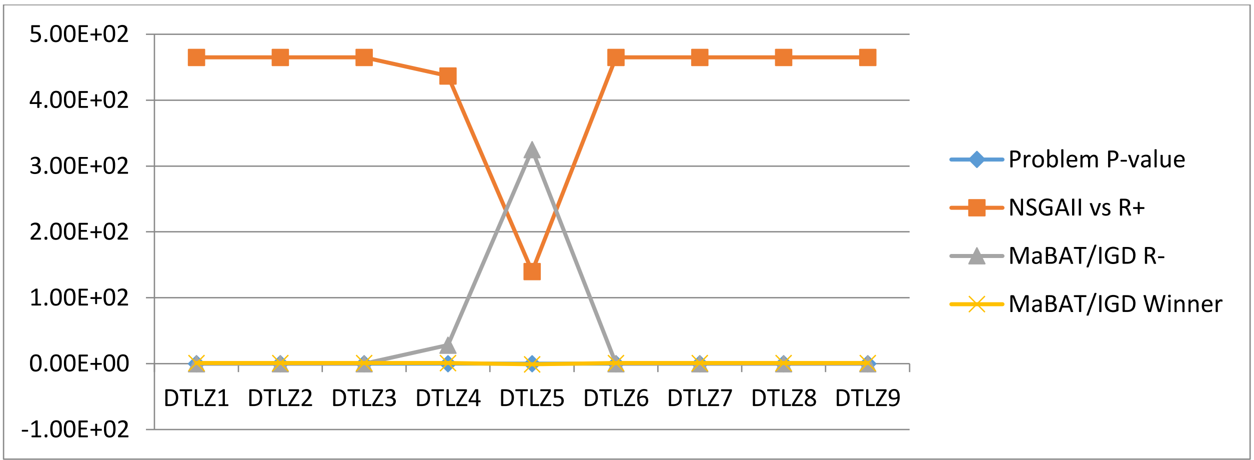

Figure 2: Number of functions VS Fitness Value Graph for HV

8- Conclusion and Future Work

This paper proposes many objective bat algorithms dependent on decay system (MaBAT/IGD), in which MOPs is deteriorated into various scalar improvement sub-issues, and each sub-issue is enhanced by just utilizing data from its few neighboring sub-issues in a solitary run. Both two execution measurements (IGD and HV), it plainly show that MaBAT/IGD is profoundly serious and even outflanks the chose MOBATs. The figures of Pareto fronts additionally show that MaBAT/IGD can deliver moderately better-disseminated Pareto fronts contrasted and the chose MOBATs.

Extra tests and examination of the proposed are exceptionally required. Later on work, we concentrate on the parametric examinations for a more extensive scope of test issues, including discrete and blended kind of improvement issues. We attempt to test the assorted variety of the Pareto front it can create in order to distinguish the approaches to improve this calculation to suit a differing scope of issues. There are a couple of productive methods to create assorted Pareto fronts, and some blend with these procedures may improve MaBAT/IGD significantly further. Further exploration can likewise underline the exhibition correlation of this calculation with other well-known techniques for multi-target enhancement. What's more, hybridization with different calculations may likewise end up being productive.

References

[1] P. A. N. Bosman and D. Thierens. (2003). the balance between proximity and diversity in multi-objective evolutionary algorithms. IEEE Transactions on Evolutionary Computation, 7(2) :{ 174,188}.

[2] M. Laumanns, E. Zitzler, and L. Thiele. (2001).On the effects of arch0iving, elitism, and density based selection in evolutionary multi-objective optimization. In Evolutionary Multi-Criterion Optimization (EMO), pages 181-196.

[3] Prakash, R., Lokeshgupta, B. and Sivasubramani, S. (2018, December). Multi-objective bat algorithm for optimal placement and sizing of DG. In 2018 20th National Power Systems Conference (NPSC) (pp. 1-6). IEEE.

[4] Yang, X. S. (2012). Bat algorithm for multi-objective optimization. ArXiv preprint arXiv: 1203.6571.

[5] Laudis, L. L., Shyam, S., Jemila, C., & Suresh, V. (2018). MOBA: Multi Objective Bat Algorithm for Combinatorial Optimization in VLSI. Procedia Computer Science, 125, 840-846.

[6] Remha, S., Chettih, S., &Arif, S. (2018). A Novel Multi-Objective Bat Algorithm for Optimal Placement and Sizing of Distributed Generation in Radial Distributed Systems. Advances in Electrical and Electronic Engineering, 15(5), 736-746.

[7] Talal R. Comparative study between the (ba) algorithm and (pso) algorithm to train (rbf) network at data classification. International Journal of Computer Applications. 2014 Jan 1; 92(5):16–22.

[8] Khan K, Sahai A. A comparison of BA, GA, PSO, BP and LM for training feed forward neural networks in e-learning context. International Journal of Intelligent Systems and Applications. 2012 Jun 1; 4(7):23.

[9] S. Mirjalili, S. Saremi, S.M. Mirjalili, L.d. S. Coelho, Multi-objective grey wolf optimizer: a novel algorithm for multi-criterion optimization, Expert Syst. Appl. 47 (2016) 106–119, doi: 10.1016/j.eswa.2015.10.039 .

[10] Qi, Y., Ma, X., Liu, F., Jiao, L., Sun, J., & Wu, J. (2014). MOEA/D with adaptive weight adjustment. Evolutionary computation, 22(2), 231-264.

[11] Q. Zhang, A. Zhou, S. Zhao, P. N. Suganthan, W. Liu, and S. Tiwari. Multi-objective optimization test instances for the CEC 2009 special session and competition. Working Report CES-487, School of CS & EE, University of Essex, 2009.

[12]Li, H., Deb, K., Zhang, Q., Suganthan, P. N., & Chen, L. (2019). Comparison between MOEA/D and NSGA-III on a set of novel many and multi-objective benchmark problems with challenging difficulties. Swarm and Evolutionary Computation, 46, 104-117.

[13] Coello, C. C., &Lechuga, M. S. (2002, May). MOPSO: A proposal for multiple objective particle swarm optimization. In Proceedings of the 2002 Congress on Evolutionary Computation. CEC'02 (Cat. No. 02TH8600) (Vol. 2, pp. 1051-1056). IEEE.

[14] E. Zitzler and L. Thiele, “Multiobjective evolutionary algorithms: A comparative case study and the strength Pareto approach,” IEEE Trans. Evol. Comput., vol. 3, no. 4, pp. 257–271, Nov. 1999.

[15] K. Li, K. Deb, Q. Zhang, S. Kwong, An evolutionary many-objective optimization algorithm based on dominance and decomposition, IEEE Transactions on Evolutionary Computation 19 (5) (2015) 694–716. doi:10.1109/TEVC.2014.2373386.

[16] Fleischer, M. (2003). The measure of Pareto optima. Applications to multi-objective metaheuristics. In Fonseca, C. M., Fleming, P. J., Zitzler, E., Deb, K., and Thiele, L., editors, Evolutionary Multi-Criterion Optimization. Second International Conference, EMO 2003, pages 519–533, Faro, Portugal. Springer. Lecture Notes in Computer Science. Volume 2632.

[17] Jacqueline Moore and Richard Chapman. Application of Particle Swarm to Multi-objective Optimization. Department of Computer Science and Software Engineering, Auburn University, 1999.