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Performance Measurement on Multi-Objective Optimization with Its Techniques

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Abstract

Multi-objective optimization (MOO) is the procedure of all the while streamlining two or all the more clashing objectives subject to specific requirements. Genuine building outlines regularly contain more than one clashing objective function, which requires a MOO approach. In a single objective optimization (SOO) issue, the ideal solution is clearly characterized, while a group of exchange offs that offers ascend to various groups exists in MOO issues. Every solution indiactes to a specific execution exchange off between the goals and can be viewed as ideal. In this paper introduces an overview on MOO and MOEA produces a solution of non-dominated (ND) solutions toward the end of run, which is called a Pareto set. An examination of Pareto strategies alongside their focal points and weaknesses and exploration take a shot at MOP utilizing distinctive systems.

***Keywords**: MOP,PSO,SA, GA*

1. Introduction

In todays time, MOO is the most powerful research topic for scientists and researchers. This is due to the MO nature of real life issues. Most real problems are complex and multidisciplinary in nature, and quite often require more than one conflicting objective function to be optimized simultaneously while usually no prior information about their exact interactions is available [1].

Researchers have developed many MOO procedures. For MOO problems, there is not a single optimum solution, but a set of ND optimal solutions called the Pareto set of solutions. The challenge is in the case of conflicting objectives, which is usually the case in most real problems.

Traditional mathematical programming techniques have some limitations when solving MOPs. Most of them depend on the shape of the Pareto front and only generate one Pareto solution from each run. Thus, several runs (with different parameter settings) are generally required to generate a Pareto solution set; however, sometimes different parameter settings may generate similar results. In such circumstances, generating a Pareto solution set will be very computationally expensive [2]. In the last two decades, most of the researchers used meta-heuristics approaches such as genetic algorithm (GA), simulated annealing (SA), tabu search (TS), particle swarm (PS) to solve the MO problems.

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2. Evolutionary Algorithm

2.1. Deterministic Meta-Heuristics

a) Tabu Search (TS)

TS [7], otherwise called Hill Climbing is basically a complex and enhanced sort of nearby pursuit, the calculation fills in as takes after: Consider a starting acknowledged solution; assess its connecting solutions in view of the acclimated adjacency structure, and set the best as the first found neighbor, which is superior to the present solution. Emphasize the capacity until the best solution is found in the area of the present solution. The limited search stops if the present solution is better every one of its neighbors.

2.2. Probabilistic Meta-Heuristics

a) Simulated annealing

SA is actuated as the most key component of meta-heuristic techniques that gives single solution and corpuscles gathering issues. City *et al*. Presented SA in 1953 [4]. It was inspired by expecting the solid activity of toughening solids. Initially, a solid is rancorous to a top temperature and again cooled exhaust so that the game plan whenever is about in thermodynamic balance. At harmony, there might be proliferating arrangements with anniversary agnate to a particular action level. The extrinsic of tolerating a change from the acknowledged agreement to another agreement is going with to the abnormality in movement in the midst of with the two states. From that point forward, SA has been comprehensively adjusted in combinatorial streamlining issues and it was demonstrated that SA has finished worthy eventual outcomes on an assortment of such issues.

b) Population based methods (PBM)

PBM are those which mimic the organic or normal event as well as furthermore set up with group of introductory reasonable solutions called "Population" and the aim is immediate, that search in state space would to reach to the most great solution. EA are the new search practices, which utilizes computational shape of method of advancement and selection[5].

i. Evolutionary Algorithms

EAs utilize the vocabulary acquired from hereditary qualities. They reproduce the development over a grouping of eras (cycles inside of an iterative procedure) of a population (set) of competing solutions. A candidate solution is inside presented to as a series of genes and is called chromosome or person. The position of a gene on a chromosome is called locus and all the conceivable qualities for the quality frame the arrangement of alleles of the separate quality. The inner representation (encoding) of an candidate solution in a EA shapes the genotype that is prepared by the transformative calculation. Every chromosome relates to a candidate solution in the inquiry space of the issue, which indicates to its phenotype. A decoding function is important to make an interpretation of the genotype into phenotype. Change and Crossover are two regularly utilized administrators alluded to as EA methodologies [6].

ii. Ant colony optimization (ACO)

The primary ACO [7] algorithm showed up in the mid 90s by was created by Dorigo is generally taking care of metaheuristic for combinatorial optimization issues. The reflection depends on the ascertainment of rummaging conduct of ants. At the point when strolling on courses from the home to a wellspring of food, the ants appear to expect a securing of a basic erratic course, yet an entirely "decent" one, in assention of shortness, or consistency, as far as time.

iii. Bees algorithm (BA)

It initially presented the BA [8] as an optimization technique empowered by the typical scavenging activities of honeybees to locate the ideal result. The marvels behind this calculation is the food scrounging conduct of honey bees. Honey bees are normally ready to prolong their state over extended spaces and in sundry likely headings, simultaneously to profit by the huge number of food sources. A colony is thrived by reallocating its foragers to their ideal fields. Regularly, more honey bees are selected for blossom patches with adequate measures of nectar or dust that can be collected with less effort.

iv. Water flow-like algorithm (WFA)

WFA was presented [9] as a nature motivated optimization for object clustering. It imitate the activity of water spilling out of higher to lower level and helps during the time spent scanning for ideal result.

v. Gravitational Search Algorithm (GSA)

In the algorithm[10] specialists are considered as objects and their execution is measured by their masses. Every one of these objects draw in one another by the gravity power, and this power causes a worldwide movement of all items towards the objects with heavier masses. Henceforth, masses collaborate utilizing an immediate type of correspondence, through gravitational force. The heavy masses – which compare to great solutions – move more gradually than lighter ones, this ensures the abuse venture of the calculation. In GSA, every mass (specialists) has four details: position, inertial mass, active gravitational mass, and deactive gravitational mass.

vi. Genetic Algorithms

GA[11]- It is based on the Theory of Natural Selection. Thus, GA mimics the real behavior of real evolutionary systems through three basic steps: Given a set of Initial Solutions S

Step 1. Selection. In this stage, choose solutions from a population. In pairs, choose two solutions x, y ∈ S

Step 2. Crossover. In this step, cross the selected solutions to avoid local optimums.

Step 3. Mutation. Bothers the new solutions found for expanding the population. The bother should be possible as per the representation of the solution. In this stage, great solutions are added to S.

vii. Particle Swarm Optimization (PSO):

PSO is a PBM finds the ideal solution utilizing a populace of particles(individual) [12]. Each swarm of PSO is an answer in the solution space. PSO is fundamentally created through the reproduction of fowl running in two-measurement space.

The PSO heuristic was initially presented [15] for the optimization of ceaseless non-linear functions. An altered populace of solutions is utilized, where every solution (or molecule) is indicated by a point in N-dimensional space. The ith molecule is regularly spoken to as.

$$X_1 = (X_1, 1; X_1, 2; :::: \cdots X_1 N)$$

and its performance evaluated on the given problem and stored.Each particle maintains knowledge of its best previous evaluated position, represented as

$$\mathrm{P}_1 = (\mathrm{P}_1, 1; \mathrm{P}_1, 2; :::: \cdots \mathrm{P}_1 \mathrm{N})$$

and additionally has learning of the single global best (gbest) solution discovered in this way, in the conventional SO application listed by g. The rate of position change of a molecule then relies on its past local best position (lbest) and the gbest, and its previous velocity. For particle i this velocity is

$$\mathrm{V_i} = (\mathrm{v_i}, 1; \mathrm{v_i}, 2; :::: \cdots \mathrm{v_i N})$$

The general algorithm for the adjustment of these velocities is:

$$V_{i,j} = wv_{i,j} + c_1 r_1 (P_{i,j} - X_{i,j}) + c_2 r_2 (Pg, j - x_{i,j})$$

$$X_{i,j} = x_{i,j} + \chi^{v}{}_{i,j}; j = 1; \dots . . N$$

Where w is the inertia of a particle, c1 and c2 are constraints on the velocity toward global and local best, χ is a constraint on the overall shift in position $\mathrm{r1; r2} \sim \mathrm{U}(0; 1)$.

During every era every molecule is quickened toward the molecule's previous best position (pbset) and the gbest position. At every emphasis new velocity value for every molecule is figured in view of its present velocity, the separation from its pbest position, and the separation from the gbest position. The new velocity value is then used to ascertain the following position of the molecule in the search space.This procedure is then iterated a set number of times, or until a minimum error is accomplished. In the inertia version of the calculation an inertia weight, lessened linearly every era, is increased by the present velocity and the other two segments are weighted arbitrarily to new velocity value for this molecule, this thus influences the following position of the molecule during the next generation.

3. Single Objective Versus Multi-Objective

3.1. Single Objective Optimization (SOO)

The main goal of SO optimization is to find the“best” solution, which corresponds to the minimum or maximum value of a SO function that lumps all different objectives into one. This type of optimization is useful as a tool which should provide decision makers with insights into the nature of the problem [13].

3.2. Multi-Objective Optimization (MOO)

In a MOO with conflicting objectives, There is no single optimal solution. The interaction among different objectives gives rise to a set of compromised solutions, largely known as the trade-off, non dominated, non inferior or Pareto-optimal solutions. MO methodologies are more likely to identify a wider range of these alternatives since they do not need to prespecify for which level of one objective a single optimal solution is obtained for another [13]. Mathematically, the MO model is defined as follows:

$\mathrm{optimize}\ \mathrm{F(X)} = \{\mathrm{f_1(X), f_2(X), \ldots\ldots, f_n(X)}\},$

Subject to:

$\mathrm{H(X)} = 0, \qquad (4_a)$

$G(X) = 0, \qquad (4_b)$

$X_1 \leq X \leq X_g \qquad (4_b)$

Where F(X) is group of objective functions, H(X) and G(X) are the requirements of the issue. Finally, Xl and Xu are the limits for the bounds of variables X. Not at all like to Mono-Objective Optimization, MOO manages seeking a group of ideal solutions rather than an ideal solution.

4. Techniques to Solve Optimization Problems

There are two techniques are used by researchers to solve MOO problems:

A. Conventional techniques and

B. Evolutionary based techniques.

The impediment of conventional methods is that it requests a former information of the issue (destinations), which may not be accessible at constantly. The EA based systems are based with respect to hereditary calculation. The fundamental point of interest of MOEAs is that they don't require any an earlier information of issue.

A. Conventional Techniques

1) Weighted Sum Technique:

This technique converts multiple objectives into SO using linear combination of objectives.

$$Y = \sum_{j=1}^{n} w_j f_j(x) \qquad (1)$$

Where, $\mathrm{w_j}$ is fractional numbers $(0 \leq \mathrm{w_j} \leq 1)$ and $\mathrm{f_j(x)}$ is jth objective function.

This method is appropriate when we know weightage of every goal of issue. Prerequisite of a former learning of weightage of every goal of an issue is a noteworthy confinement of this method [14].

2) Constraint Based Technique

This system considers one and only objective at once and regards remaining k-1 objectives as imperatives. This procedure applies on all goals one by one. Last answer is processed by taking normal of results acquired for all objectives. Utilization of this procedure requests an earlier learning of requirements of the issue.

B. Evolutionary Based Techniques (EBT)

EBT utilize the idea of GA and takes care of the MOO issue. A study on the open issues and diverse ways to deal with tackle these issues in the field of EA is introduced in [15],[16]. Taking after are the progressions of MOEA:

Step1 Initialization: Start with a random population based on the given population size.

Step2 Fitness assignment: assign a rank to each individual of the population for generating a mating pool.

Step3 Variation: apply variation operators (crossover, mutation) on the mating pool to generate new solutions.

Step4 Environmental selection: select the best solutions according to the size of mating pool for next generation.

Step5 Repeat above procedure until termination criterion meets. The following termination criteria can be used: stop after maximum number of generations, stop when algorithm succeeds in solving the problem.

5. Multi-Objective Evolutionary Algorithms (MOEA)

5.1. Non-Elitist Multi-Objective Evolutionary Algorithms

1) MOGA

Multi Objective Genetic Algorithm (MOGA) [17]. The rank to an individual is assigned taking into account the quantity of solutions in the populace by which it is dominated. All ND solutions are assigned the same fitness value. The fitness sharing system discovers closeness among various solutions in light of the separation between fitness estimations of these solutions. The procedure minimizes the fitness estimations of solutions having a place with thick region of solutions pursuit space. Along these lines, it permits investigation of solutions in unexplored pursuit region of solution search space. As fitness sharing procedure needs to discover comparative solution, it requires additional computational time. Along these lines, the joining rate of MOGA is moderate.

2) NSGA

Non-Dominated Sorting Genetic Algorithm (NSGA) [18]. Before selecting people for mating, the populace is positioned taking into account non-domination: all ND solutions are characterized into one classification and assigned dummy fitness gives equivalents to the span of populace. This dummy fitness gives parallel regenerative opportunity to all the ND solutions. Keeping in mind the end goal to keep up the differences of the populace; these classified solutions are imparted to their dummy fitness values. At that point this gathering of grouped solutions is overlooked and another layer of ND solution is considered. The procedure proceeds until all people in the populace are arranged. This calculation is not exceptionally effective on the grounds that it requires investment O(MN3) where, M is the quantity of the goals and N is the populace size.

4.2. Elitist Multi-Objective Evolutionary Algorithms

1) NSGAII

NSGAII [19]. It is an improved version of NSGA [6]. The rank of every solution is computed based on how many number of solutions it dominates. In order to maintain the diversity of a population the algorithm finds average distance of two neighbors on either side of a solution along each of the objectives (as shown in Figure 2). The calculated distance is called crowding distance of that solution. For generating mating pool for next generation, selection of solutions is performed based on rank and crowding distance. When two solutions have the same rank then a solution that has higher crowding distance is selected for mating. The algorithm selects the solutions for the next generation based on following policy: select best solutions out of union of the best parents and best offspring (obtained after application of genetic operators). The following criteria are used for selection of the best solutions from the union: fitness and spread. As the algorithm selects the best solutions from the union, it does not require extra memory to preserve elite solutions.

2) SPEA

Strength Pareto Evolutionary Algorithm (SPEA) [20]. The SPEA presented elitism by maintaing outer document (N') to store already discovered ND solutions. The fitness task procedure of SPEA has two stages: (i) solutions in the outer document set are positioned in light of non-domination. For every solution having a place with the outside document set, appoint the quality worth utilizing the equation Si=n/N+1 where, n is the quantity of people of populace which are commanded by the solution i and N is the measure of populace. (ii) people in populace are assessed. The fitness of an individual j taking so as to have a place with populace is computed whole of the quality estimations of all solutions of file (N') that is dominated by j. The best solutions as indicated by fitness qualities are chosen from union of N+N' for producing the mating pool for the size of population. At the point when outside document gets full, truncation is performed in view of agglomerative normal linkage based clustering technique.

3) SPEA2

SPEA2[22] is an improved version of SPEA [20]. It is different from SPEA in two viewpoints: fitness task plan and diversity technique. SPEA2 computes fitness of an individual in view of summation of: (1) what number of people commands it and (2) what number of different people dominated by it. The SPEA utilizes clustering based diversity strategy which may not safeguard amazing (fringe) solutions Though, SPEA2 utilizes closest neighbor estimation procedure for protecting arrangement differing qualities.

4) PAES

Pareto Archive Evolutionary Strategy (PAES [21]. This calculation keeps up outside document to store already discovered ND arrangements. In this calculation, mating is performed between two parents to create a single offspring, the principal parent is chosen from current populace and the second is chosen from the outside archive (beforehand discovered ND solutions). In the event that recently created offspring rules the parent chose from outside archive then the parent is replaced by the offspring. Diversity is kept up by isolating objective space in matrix.

Table 1. Shows Different Algorithms with Advantages and Disadvantages

Algorithm	**Fitness *Assignment***	***Advantages***	***Disadvantages***
NSGA[18]	Ranks are assigned based on sorting of non - dominated solutions	Converges fast towards Pareto *front*	Pareto ranking need to be repeated over *and over again*

NSGAII[19]	Ranks are assigned based on sorting of noominated solutions	It gives good performance on two objectives *problems*	Does not perform well on problems with two or more *objectives*
SPEA[20]	Rank of solution is calculated based on summation of strength value of solutions in external archive	No need to define any parameter for *Clustering*	Agglomerative hierarchical clustering takes more time and extreme solutions may not get *preserved*
SPEA2[21]	It calculates rank of an individual based on summation of :(1) how many individuals dominates it and (2) how many other individuals dominated by it	Extreme solutions are *preserved*	Rank assignment and diversity preservation methods are more *time consuming*

6. Applications of MOEA

- Aerospace Engineering
- Data Mining
- Software Engineering
- Flowshop and Jobshop Scheduling Problem.
- Electrical/ Electromagnetic/ Electronics Engineering
- Image Processing

7. Literature Survey

Feng *et al.* [23] In this paper, it propose a teaching-learning-based optimization algorithm for MOO problems. MOTLBO adopt the ND sorting concept and the mechanism of crowding distance computation. The Pareto fronts of the solutions are guided by the teacher which is the best learner and the mean of learners achieved so far. The efficiency and effectiveness of the proposed MOTLBO are evaluated using 6 unconstrained benchmark test problems with convex and nonconvex objective functions and 2 constrained real-word MO problems. The result of the proposed MOTLBO algorithm is a challenging method for MOO problems.

Ramadan *et al.* [1] In this paper it has presented a hybrid approach based o scatter search and SA to solve the MOO problems. Different test problems were used to compare the performance of our approach with other approaches. The results show that proposed approach is effective and competitive with the other developed approaches.

M. Balasubbareddy *et al.* [24].A novel improvement method is proposed to take care of SOO and MOO issues with era fuel cost, and aggregate force misfortunes as goals. This technique is a hybridization of the routine cuckoo search algorithm (CSA) and arithmetic crossover operations. Along these lines, the non-linear, non-convex objective function can be fathomed under viable limitations. The adequacy of this method is broke down for different cases to show the impact of functional limitations on the objective improvement. Two and three objective MOO issues are defined and settled utilizing this technique ND sorting-based hybrid CSA. The viability of this technique in limiting the Pareto front solutions in the solution district is examined. The outcomes for SOO and MOO issues are physically translated on standard test functions.

D. Cai *et al*. [25]A new MOPSO algorithm in view of disintegration of the goal space (MPSO/D) is proposed for taking care of MOO issues. The updated system in light of decay is proposed to make every sub-area in the objective space have a Pareto ideal solution. This update methodology can keep up entirely well the diversity of the acquired solutions, and the differing qualities is crucial for understanding MOPs.

Elias D. Nino *et al*. [26] In this paper expresses a novel crossover metaheuristic taking into account deterministic swapping, EA and SA inspired algorithms for the MOO of combinatorial issues. The proposed calculation is named EMSA. It is a change of MODS calculation. Dissimilar to MODS, EMSA works utilizing a pursuit heading given by the meeting of weights to every objective function of the combinatorial issue to optimization. Finally, EMSA is tried utilizing surely understand occasions of the Bi-Objective Traveling Salesman Problem (BTSP) from TSPLIB. Its outcomes were contrasted and MODS metaheuristic (its antecedent). The correlation was made utilizing measurements from the specific writing, for example, Spacing, Generational Distance, Inverse Generational Distance and ND Generation Vectors. For each situation, the EMSA results on the measurements were constantly better and in some of those cases, the predominance was 100%.

T. Liu *et al*. [27] In this paper, through examining the attributes of the oil–gas creation prepare, a MOO model is built up to augment general oil generation of the piece, minimize general water creation and far reaching vitality utilization for per ton oil, and NSGA-II calculation is utilized to tackle the proposed advancement model. Keeping in mind the end goal to promote enhance the diversity and joining of Pareto optimal solution got by NSGA-II calculation, an enhanced NSGA-II (I-NSGA-II) calculation is proposed. The calculation depends on NSGA-II calculation, another hybrid chaotic mapping model is initially settled to introduce population for keeping the beginning population diversity. At that point, the hybrid administrator is created to deliver new generation of populace for enhancing the pursuit ability of NSGA-II calculation. At long last, substitution operation of chaotic populace competitor is presented for keeping up the diversity and uniformity of got Pareto optimal solution set. The outcomes demonstrate that the Pareto ideal arrangement set got by I-NSGA-II calculation has a superior differing diversity, uniformity and convergence. In this manner, the proposed improvement strategy gives a more solid instrument to the usage of advancement control in oil generation process.

R. Venkata Rao *et al.* [28] MOO is a vital examination range in building concentrates on, in light of the fact that genuine outline issues require the advancement of a gathering of goals. Adding more than one objective to an improvement issue includes complexity.In this paper, the execution of the TLBO calculation was checked with surely understood other advancement strategies, for example, AMGAClustering MOEA, DECMOSA-SQP, DMOEADD, GDE3, LiuLi Algorithm, MOEAD, MOEADGM, and so forth by trying different things with various MO unconstrained and constrained benchmark functions. The test results demonstrate that the TLBO performs intensely with other optimization techniques reported in the writing. In this way, the TLBO calculation is powerful and hearty and has an incredible potential for tackling MO issues.paragraphs.

8. Problem Statment

Various problems that are faced in optimization are :

1. Problem of class with different comparable number of conflicting objective solution.
2. The solutions to the statistical problems are complex.
3. The population generated by various methods is not much effective.
4. These methods do not guarantee the optimized results only.

9. Performance Measures

9.1. Hypervolume (HV)

The HV measures the HV of multi-dimensional area encased by Pareto front (PF). It is utilized to demonstrate the merging towards ideal PF. Higher estimation of HV measure speaks to better solution [29].

9.2. Generational Distance (GD)

The GD metric represent value of how far approximation Pareto set is from optimal Pareto set. It is defined as

$$\sqrt{\frac{\left(\sum_{i=1}^{n} d_i^p\right)^{1/p}}{n}}$$

Where, n is the quantity of solutions in estimation set, p=2, furthermore, di is the Euclidian separation in objective space between every vector and closest neighbor of ideal PF. Lower estimation of GD measure shows better solution[30].

9.3. Maximum Pareto Front Error (MPFE)

Using MPFE we can find the convergence of algorithm. It is defined as

$$max_j(max_j(min_i min_i \left|f_1^i(\vec{x}) - f_1^j(\vec{x})\right|^p + \left|f_2^i(\vec{x}) - f_2^i(\vec{x})\right|^p)^{1/p}$$

Where i=1 to ni are the number of solutions in approximated Pareto front, j=1 to nj are the number of solutions in optimal Pareto front and p=2. Lower value of MPFE indicates better solution [30].

9.4. Test Function

9.4.1 ZDT1 Function

The ZDT1 function has a convex Pareto-optimal front. The objective functions are:

$$f_1(x) = x_1$$

$$f_2(x) = g(x)\left[1 - \sqrt{\frac{x_1}{g(x)}}\right]$$

Where g(x) is defined as:

$$g(x) = 1 + 9(\sum_{i=2}^{n} \frac{x_i}{(n-1)}$$

In this ZDT1 function, thirty design variables x_i were chosen (n=30). Each design variable ranged in value from 0 to 1.

9.4.2 ZDT2 Function

The ZDT2 function has a non-convex Pareto-optimal front. The objective functions are:

$$f_1(x) = x_1$$

$$f_2(x) = g(x)\left[1 - \left(\frac{x_1}{g(x)}\right)^2\right]$$

Where g(x) is defined as:

$$g(x) = 1 + 9(\sum_{i=2}^{n} \frac{x_i}{(n-1)}$$

In this ZDT function, thirty design variables x_i were chosen (n=30). Each design variable ranged in value from 0 to 1.

9.4.3 ZDT3 Function

The ZDT3 function adds a discreteness feature to the front. Its Pareto-optimal front consists of several noncontiguous convex parts. The introduction of a sine function in this objective function causes discontinuities in the Pareto-optimal front, but not in the parameter space. The objective functions are:

$$f_1(x) = x_1$$

$$f_2(x) = g(x)\left[1 - \sqrt{\frac{x_1}{g(x)}} - \frac{x_1}{g(x)}\sin(10\pi x_1)\right]$$

In this ZDT3 function, thirty design variables x_i were chosen (n=30). Each design variable ranged in value from 0 to 1.

In this work we invstigate the performance of MOO on ZDT1, ZDT2, ZDT3 test problems. The results are calculated on these functions. Three popular performance measure used is Hypervolume (I_{HV}) [15]. When I_{HV} is higher, the convergence and diversity of the found solutions is better.

Table 2. Results of NSGA2 on IHV

Iteration	**ZDT1**	**ZDT2**	**ZDT3**
100	-4.66	-5.10	-4.590
150	-1.835	-3.644	-1.960
200	-1.404	-5.535	-2.088
250	-2.694	3.022	-1.931

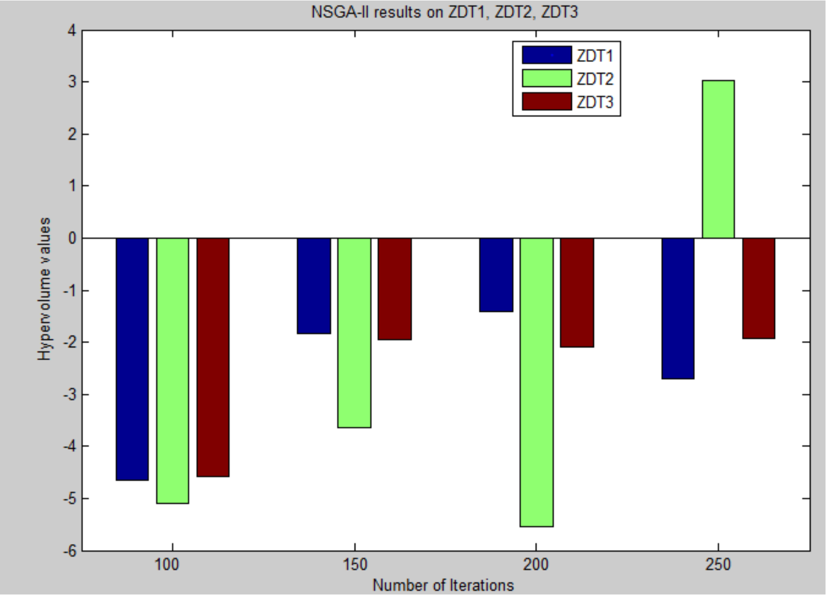

Figure 1. Graph of NSGA2 on IHV and Different Test Problems

Table 2. Results of SPEA2 on IHV

Iteration	ZDT1	ZDT2	ZDT3
100	0.343	0.61	0.176
150	0.42	0.577	0.170
200	0.365	0.563	0.191
250	0.398	0.564	0.074

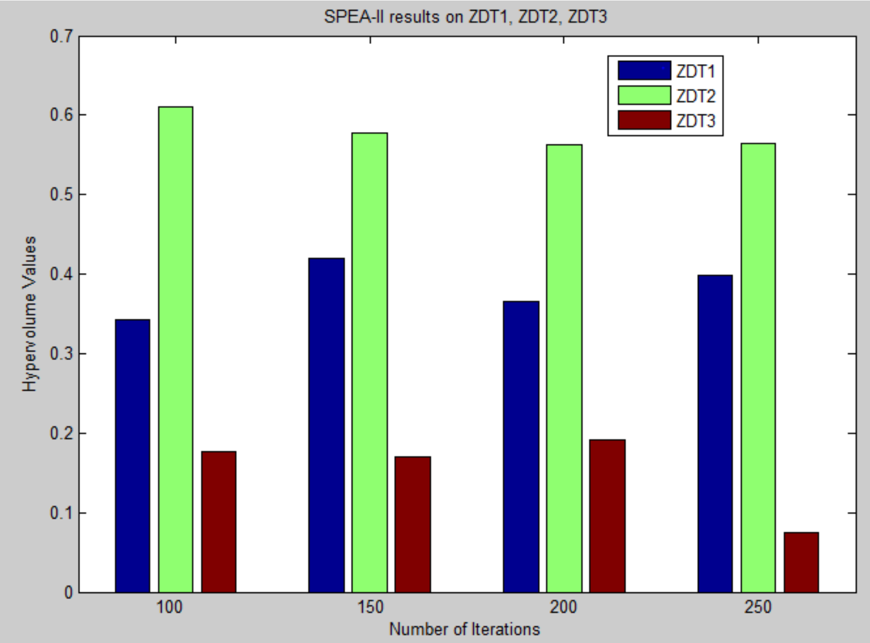

Figure 2. Graph of SPEA2 on IHV and Different Test Problems

10. Conclusion

Multi-objective are those problems consists or more objectives that is required to optimized simultaneously. In this paper present a review on Mutiobjective Evolutinary algorithm overview with the test problems and algorithms to find the optimal solution outcomes. For this we evaluate the results of test function on different number of iterations with algorithms *i.e* NSGA-II and SPEA-II. The results of SPEA-II algorithms improved result on Multiobjective problems on performance parameter hyper volume, where as NSGA-II results doesn,t work well on MOPSO .With this review in future work, we can enhance the problem of MOPSO by solving using Simmulated Anealing. By this problem of convergence and space problem be solved.

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