

Using Gravitational Search Algorithm for Solving Optimization Problems Based on Hypervolume Indicator

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Abstract. Extended utilization of adaptive algorithms, Evaluative Algorithms (EAs), to address these issues offers a way to handle massive Mult objective optimization, even if the algorithmic method for handling combinations of objectives (CO) has been accessible for quite some time. Combining the idea of superiority with the Hypervolume (HV) tag approach, the BAT algorithm utilizes various target effects to explain several algorithms depending on the Hypervolume (HV) spacing. The Mult objective Gravitational Search Algorithm with Hypervolume (MOGSA/HV). Since rapid convergence could result from bat foundation work, Hypervolume rewrites the Mult objective problem (MOP) as a sequence of Tchebycheff solutions, improving it. Since the one in charge has already decided to utilize this method (Tchebycheff) as a benchmark, solving all of the (MOGSA/HV) problems simultaneously is a formidable challenge.

In leader group construction, non-dominant groups are significant in containing less dense areas, avoiding nearby regions, and producing a more diversified and compact Pareto Frontier. This outcome was produced using nine conventional nonlinear functions. It might seem that MOGSA/HV outperforms Mult objective Evolving Algorithm under Dincity Indicator (MOEAD), Non-Sorting Genetic Algorithm Two (NSGAI), Multi-Partical Swarm Optimization under Distance Indicator (MPSOD), and Spacing Evolving Algorithm Two (SPEA2).

The results we obtained showed the efficiency of the new algorithm compared to other algorithms, which was based on its convergence to the optimal solution based on the (HV). Every single end product was created using MATLAB (R2020b).

Keywords. Mult objective Problems, Gravitational Search Algorithm, Hyper Volume Indicator.

INTRODUCTION

Here, we will discuss the present research, which is one of the many essential investigations of the last few decades, and outline its study's aims, inquiries, relevance, scope, and limits.

When optimizing for many objectives, efficient Pareto solutions are more common than one-size-fits-all solutions. Cluster sampling becomes crucial when co-optimizing an algorithm to produce a thorough and diverse approximation of the Pareto front [1], [2]. A Mult objective Gravitational Search Algorithm (MOGSA) is presented to find the best Pareto arrangement for Mult objective Functions (MO) by utilizing the law to modify weights.

Both the Mult objective Gravitational Search Algorithm (MOGSA) and GSA, an approach to solving issues with several objectives, were introduced in the source [3]. To confirm this, we will initially create systems that can be tested using just a portion of the Mult objective assessment tasks. Next, we'll put it into practice to solve problems with technological improvements, such as the whole and partial titanium beam.

The work was accomplished using a publication-approach-based multifunction GSA algorithm (MOGSA), which has been characterized as an effective biologically motivated algorithm for addressing the floor design challenge in VSLI design [4]. [5] The second suggested using a Mult objective Optimization Problem (MOOP), or a flexible optimization challenge, to do both. The GSA technique is an innovative, easy-to-understand optimization technique that utilizes the Weight Summation Method (WSM) to solve the MOOP. According to the research available, no prior study has integrated MOGSA with the HV index.

Furthermore, a different study compared frontal network consuming algorithms with gradient-descent techniques (Backpropagation and Levenberg-Marquardt). The study also tested all three based on populations' statistically inductive methods: optimization for particle swarms, genetics, and the batting technique. Regarding training forward-looking neural networks, the bat method stands head and shoulders above the competition [6]. These findings support the idea that future trials should employ the most current cutting-edge methods, which were crucial in determining the greatest possible outcome.

One benefit of the bat algorithm is that it facilitates population analysis and neighborhood search strategies for solution discovery. Significant to creative approaches, this work brought global variety and rigorous local separation. So, not only was the velocity and volume controlled, but the BAT algorithm was also mixed with Practical Swarm Optimization (PSO) and local search techniques [7].

By modifying the reference groups method, MOGSA provided Many Objective Problems (MaOPs) with a happy medium between divergence and integration, which is the core problem of MaOPs. Sheah, R. and Abass, I.T. studied and used a new method depending on a nonlinear programming problem in 2021 as well [8]. To address the issue of Mult objective optimization, a meeting heuristic combination was suggested in 2020 [9].

In light of the foregoing, we infer that the primary aim of this research is to enhance the efficiency of Mult objective algorithms by creating an innovative approach for optimizing with multiple goals that take their cues from bats and employ a strategy to attain organization, objectives, and variety. In this work, we suggested an incremental approach that depends on the HV index proximity algorithm to decrease processing requirements in various objective challenges. The research was divided into the following sections, in order: The second section addresses the basic concepts related to the topic. The third section addresses the proposed new method. The fourth section discusses the proposed results, mentioning the main laws and basic criteria used for comparison and presenting the results in a scientifically sound. The final section contains the main conclusions and future work.

BASIC CONCEPTS

This area will begin with a generalized version of the optimization with multiple goals problem, followed by definitions and key points about the research's central topic. This leads us to the Mathematical structure of the issue:

$$\text{Minimize } F_i(x) = [f_1(x), f_2(x), \dots, f_k(x)]. \quad \dots (1)$$

Subject to:

$$w_i(x) \leq 0, i = 1, \dots, m; \quad \dots (2)$$

$$n_l(x) = 0, l = 1, \dots, p; \quad \dots (3)$$

The target factors were represented by $F_i: R^n \rightarrow R; i = 1, \dots, k$ and $w; n_j: R^n \rightarrow R, i = 1, \dots, m, \text{ and } l = 1, \dots, p$ in the statement $x = [x_1: x_2, \dots, x_n]^T$. Do you have any issues with restriction functions? We shall utilize a few of the subsequent principles to explain the overall idea of optimizing:

Definition 1 [10]: An issue involving the improvement of many objectives. The components of Mult objective programming (*MOP*) include decision variables, efficiency methods, and restrictions. The optimization techniques and objectives determine the roles and restrictions of establishing variables.

Definition 2 [10]: (Allocative efficiency- efficiency, efficiency-the greatest efficiency)
 a factor of discretion x is homotopic to X_f Completely non-empty sets are defined as $A \subseteq X_f$ iff $\nexists a \in A : a > x$.

Leave this part out if the intended set A can be inferred from the context. When x is not controlled by X_f We say that it is Allocative Efficiency-Optimal.

Definition 3 [10]: If there is no $x_2 \in X$ such that $f(x_2) < f(x_1)$, then the collection of decision variables in the variable $x_1 \in X \subset R^n$ It is not dominant concerning X .

Definition 4 [10]: The following is the definition of the Allocative Effectiveness of the most effective set P^* : $P^* = \{x_1 \in F : x_1 \text{ is a variable}\}$

Definition 5 [10]: {Allocative Performance most effective}.

The set of variables P^* , which represents the ideal distribution of resources, is defined as $\{x_1 \in F : x_1 \text{ One is allocation effectiveness optimal.}$

SUGGESTED METHOD

Throughout this part, we, as a species, will introduce the updated methodology that takes R_2 Indicator, either as an attribute or an influencer, must be considered to determine the best value to utilize when selecting the winner.

It is well-known that bats, creatures with wings, can utilize echolocation. There are over 996 various kinds of BATS in the world, making up almost 20% of the variety of well-evolved primates [8]. Depending on the swarm idea, another enhanced calculation known as GSA [11], [12]. It is possible to mimic the echolocation to find a more miniature, horizontal bat using GSA. Its main advantages are the technique's simplicity, adaptability, and utilization flexibility. In addition, the method handles a wide variety of problems well, even extremely unpredictable ones. In addition, GSA offers an ideal setup that effectively solves complicated issues in a short amount of time. Some of the problems with this estimate that can arise from trying to follow up are: The concatenation process starts fast and then slows down. On top of that, there has been no research connecting variables to different rates. Using the most cutting-edge tools, we have developed a strategy that is preferable to multifaceted capability.

The uncontrollable yet perfectly adequate structures are up to the cluster to sustain and re-establish. When determining MOGSA/HV, the most natural arrangement that can be seen is utilized. Using this method, individuals will relocate to get a better solution close to the optimal arrangement. However, it is completely impartial regarding space, opposing Pareto's top recommendations. To solve the research challenge, the Pioneer Selection element was built. A single book documents the most logical and non-dominant combinations. The person in charge chooses an item from the stacking area arrangement components and proposes a non-dominant alternative. Through the help of the arbitrary wheel and the possibilities that are accessible to each person, the right choice is made. Here are the detailed instructions for building the suggested algorithm, emphasizing the part that utilizes the HV ideal value choosing.

Steps of new methods (MOGSA/HV)

With $k := 0$ and velocity = 0, $\mu = 0.1$, $r_0 = 0.5$, and $A = 0.6$, define the initial conditions.

You can reload the point at will. For the population of n , P_i ;

The initial nation's model parameters are $f(P)$;

Find alternatives that aren't dominating and utilize them to kick off the storage.

However, the withdrawal criteria have not been satisfied.

GSA Steps

Initialization of Agents

- Randomly generate positions for N agents in the D -dimensional search space.
- Initialize velocities to zero for all agents

Fitness Evaluation

- The goal function should be utilized to determine the efficiency value of each entity.
- Identify (best(t)) and (worst(t)) fitness values:

$$best(t) = \max(fit_i(t)), worst(t) = \min(fit_i(t))$$

Gravitational Constant Update

- Time-dependent reduction of gravitational constant $G(t)$:

$$G(t) = G_0 \cdot e^{-\alpha t/T}$$

Where G_0 = initial value, α = decay rate, T = maximum iterations

Mass Calculation

- Convert fitness values to normalized masses:

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)}$$

Force Calculation

- Compute the total gravitational force on each agent:

$$F_i^d(t) = \sum_{j \in K_{best}} G(t) \frac{m_i(t) \cdot m_j(t)}{R_{ij}(t) + \epsilon} (x_j^d(t) - x_i^d(t))$$

Where R_{ij} = Euclidean distance, K_{best} = top agents

Acceleration & Velocity Update

- Calculate acceleration using Newton's second law:

$$a_i^d(t) = \frac{F_i^d(t)}{m_i(t)}$$

- Update velocity with random coefficient $\alpha = 1$:

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1)$$

Position Update

- Move agents using updated velocities.

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1)$$

End

EXPERIMENTAL RESULTS

This section will show some of the most significant outcomes of the suggested algorithm MOGSA/HV, better than other computations that utilized the famous test problem (DTLZ) operations. We only utilized nine functions for this

analysis, and they varied in size regarding instructions, target operations, and recurrence. The issues with uneven PF trends are fundamental to consider.

In this study, we utilize recognized HV [13] and [14] and Inverted Generation separation (IGD) [15] and [8] as evaluation criteria. You want to see how diverse and focused the techniques' ideal end product set is, you can utilize either HV or IGD. A higher HV score or lower IGD number suggested a higher resemblance to that initial PF. When determining HV, using an indicator location where real PF predominates is standard practice.

Inverted Generational Distance (IGD)

Allowing the MOEA to stand for the MOEA's searching outcome on a particular MOP. The set R should comprise equally spaced objects representing the PF. The IGD quantity S concerning R may be found using [1], [16] and [17].

$$IGD(S, R) = \frac{\sum_{r \in R} d(r, S)}{|R|} \quad \dots (4)$$

If the circularity of R is represented by |R| and the minimal distance determined by Euclid between r and every point in S is described as d(r, S), etc. A sufficiently tremendous value of |R| and an equitable distribution of R's components are necessary conditions for R's data points to reflect the PF accurately. This guarantees that the convergence and diversity of the end product set may be appropriately evaluated by the IGD, with a lower IGD number for S, which means it's a better-quality product [18], [19] and [20].

In the next section, you must supply a set R of PF indicating endpoints to compute the IGD value of an end product set S from an MOEA running on a MOP.

Hypervolume Indicator

Determine the amount of space in region H using the hyperbolic amount symbol $I_{hyp}(\mathcal{A})$. This region H comprises points A and N, which are points of view. (i.e., Hypervolume measures the size of the objective function space dominated by solutions S and bounded by I_{hyp} .)

$$I_{hyp}(\mathcal{A}) = \text{volume} \left(\bigcup_{\forall a \in \mathcal{A}; \forall n \in \mathcal{N}} \text{hypercube}(a, n) \right) \quad \dots(5)$$

Therefore, better choices are indicated by larger suggestive values. Hypertensive statistics go under several names, including the S metrics and the Lebesgue measure. Many people find it appealing, and that's helped it gain popularity and prosperity. For example, it is a Pareto monotone and the sole indicator with metric properties [21]. Due to these features, this metric has found utility in several contexts, such as performance evaluation and evolutionary computing.

ANALYSIS END PRODUCTS

This section will offer the best technique assessments and entry points utilizing the Wilcoxon Proficiency Admission Test Measure, a reliable statistical instrument.

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Assessment of positions by comparing two images using the Wilcoxon indicated orientation test, we can find out how different they are [22] and [23]. We may decide whether to conduct an optional territory experiment based on the extent and indications of these differences. The present investigation investigates the subsequent hypotheses:

$$H_0 : m = m_0 \quad , \quad H_A : m > m_0 \text{ or } H_A : m < m_0 \text{ or } H_A : m \neq m_0 \quad \dots(6)$$

Where the Null hypothesis H_0 and One-sided alternative hypothesis H_A Against any of the possible alternative hypotheses. In addition, this metric is utilized to find out which forecast is better. For the i^{th} problem out of n , let d_i be the difference in appearance scores comparing the two computations. For cases when the primary computation is faster than the second, allow R^+ To represent the sum of sites. At last, R^- Should handle the number of areas where the subsequent estimate performs better than the prior one. The entireties are fairly distributed with several zeroes. An odd number indicates that just one of these sums was recently eliminated.

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

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

.....(7)

To try to compare the formulas at a high level of $alpha = 0.05$, we utilize MATLAB to determine the p-value. When the p-value is not just the crucial component, the idea of a null is invalidated. Using several different test configurations, R^+ Handles a high mean estimate that shows superiority over planning procedures. Across the board, our approach beats the competition. Regardless, no other Research approach can reach $R^+ = \frac{n*(n+1)}{2}$.

END PRODUCTS AND DISCUSSION

During this part, we will discuss and verify which algorithms are superior to others. Matlab carried out a classic problem-specific implementation of the multi-target bat calculation (MOGSA/HV) with decaying. The total number of variations, rate of accessible limitation β , and population size (n) are some items examined using the suggested technique.

An approach was suggested for balancing convergence and variety, and the findings were utilized to align with it. However, to find the best solution, we contrasted MOGSA/HV against two multi-target PSO financial records to learn its strength and degree of. MOEA/D [11] and MOPSO [24] are distinct approaches. Each computation is executed many times to obtain measurements of (IGD) and (HV) for every test run.

Table 1: Presented here are both the mean and the standard deviation of the GD values for five, ten, fifteen, and twenty objective issues on (DTLZ1 to TLZ9), as well as for six just lately compared techniques: IBEA, BiGE, MOMBIII, MODEMR, KnEA, RVEA, and MOGSA/HV.

Problems	N	M	D	FEs	IBEA	BiGE	MOMBIII	MODEMR	KnEA	RVEA	MOGSA/HV
DTLZ1	150	5	9	150000	1.3095e-1 (1.15e-2)	5.8661e-2 (1.30e-2)	3.3205e-2 (1.22e-3)	6.4069e-2 (2.08e-2) -	1.0114e-1 (2.94e-2)	4.4514e-2 (2.37e-4)	4.2967e-2 (3.10e-4)
	200	10	14	200000	1.4518e-1 (4.38e-4)	3.7500e-2 (1.17e-1)	1.8021e-1 (5.75e-2)	1.2591e-1 (9.03e-3) -	7.5311e-2 (5.96e-4)	1.6463e-1 (1.82e-2)	1.2284e-3 (2.99e-2)
	250	15	19	250000	1.6128e-1 (9.26e-3)	1.1209e-2 (5.06e-3)	1.8270e-1 (1.26e-2)	1.0389e-1 (1.75e-2) -	1.0010e-1 (6.67e-4)	1.7451e-1 (1.31e-2)	4.1108e-3 (3.72e-2)
	300	20	24	300000	1.0682e-1 (6.46e-3)	7.3912e-3 (4.59e-3)	2.3354e-1 (7.60e-3)	1.6353e-1 (2.19e-3) -	1.4777e-1 (3.48e-4)	1.2063e-1 (1.11e-2)	2.0028e-4 (2.11e-3)
					-	-	-	-	-	-	-
DTLZ2	150	5	14	150000	1.0626e-1 (1.91e-3)	1.7552e-1 (9.76e-3)	1.3635e-1 (6.31e-4)	1.2658e-1 (5.14e-3) -	1.4002e-1 (4.59e-3)	1.3516e-1 (1.90e-4)	1.3636e-1 (3.75e-4)
	200	10	19	200000	2.7959e-1 (7.68e-3)	2.9734e-1 (9.61e-3)	4.1893e-1 (1.39e-1)	2.3533e-1 (3.62e-3) =	2.7217e-1 (2.75e-3)	2.5449e-1 (2.37e-3)	3.2484e-1 (4.38e-3)
	250	15	24	250000	3.7548e-1 (7.09e-3)	4.0092e-1 (1.11e-2)	5.5144e-1 (8.18e-1)	4.6417e-1 (2.68e-3) -	3.4223e-1 (5.49e-2)	3.8500e-1 (7.09e-3)	4.2505e-1 (4.65e-3)
	300	20	29	300000	4.2117e-1 (1.01e-2)	4.2866e-1 (9.26e-3)	6.4734e-1 (3.23e-1)	3.0254e-1 (2.05e-1) -	3.6910e-1 (4.93e-2)	4.4603e-1 (8.40e-3)	5.5173e-1 (5.79e-2)
					-	-	-	-	=	-	-
DTLZ3	150	5	14	150000	4.5877e-1 (5.33e-3)	1.8701e-1 (6.83e-2)	1.3570e-1 (1.54e-3)	3.2453e-1 (2.22e-1) -	1.5969e-1 (1.32e-1)	7.2283e-2 (5.94e-2)	1.3552e-1 (6.96e-3)
	200	10	19	200000	5.4740e-1 (8.85e-3)	7.0613e-2 (1.67e-2)	6.7595e-1 (3.91e-1)	7.2244e-1 (1.40e-3) -	2.2335e-1 (2.03e-2)	4.3100e-1 (1.71e-2)	7.0652e-3 (2.02e-1)
	250	15	24	250000	6.3131e-1 (1.33e-2)	5.4282e-2 (1.11e-2)	7.2924e-1 (2.00e-1)	8.5999e-1 (5.10e-4) -	3.2224e-1 (2.17e-2)	6.9239e-1 (2.05e-2)	5.8071e-4 (2.38e-2)
	300	20	29	300000	6.3625e-1 (1.98e-2)	2.3031e-3 (1.93e-3)	7.6704e-1 (2.34e-2)	8.7073e-1 (1.76e-3) -	4.5596e-1 (1.48e-2)	6.1768e-1 (9.65e-1)	4.6332e-4 (5.81e-3)
					-	-	-	-	-	-	-
DTLZ4	150	5	14	150000	1.2991e-1 (8.11e-2)	1.7122e-1 (9.52e-3)	1.5227e-1 (5.82e-2)	1.4463e-1 (7.82e-2) -	1.3813e-1 (5.82e-3)	1.3757e-1 (2.62e-3)	1.4400e-1 (5.19e-1)
	200	10	19	200000	2.6277e-1 (2.28e-1)	2.8466e-1 (1.38e-1)	3.1262e-1 (4.50e-3)	3.1621e-1 (1.32e-1) -	2.9495e-1 (6.14e-3)	3.1605e-1 (4.27e-3)	2.3753e-1 (4.22e-2)
	250	15	24	250000	3.5666e-1 (7.01e-2)	3.4357e-1 (1.76e-1)	4.0163e-1 (7.60e-2)	4.4929e-1 (4.11e-3) -	3.7925e-1 (3.57e-3)	4.1835e-1 (2.36e-3)	4.3216e-1 (3.71e-2)
	300	20	29	300000	4.2320e-1 (8.56e-3)	3.5429e-1 (1.75e-2)	4.5593e-1 (4.89e-3)	4.8632e-1 (6.55e-3) -	4.2006e-1 (1.78e-3)	4.5332e-1 (2.96e-5)	5.5216e-1 (5.18e-2)
					-	=	-	-	-	-	-
DTLZ5	150	5	14	150000	1.2986e-2 (5.92e-3)	1.4416e-2 (4.57e-3)	1.7996e-1 (2.48e-1)	5.2321e-1 (3.42e-16)	1.1265e-2 (7.08e-2)	2.8491e-2 (8.46e-3)	7.2400e-1 (6.11e-1)
	200	10	19	200000	2.8386e-2 (6.25e-3)	2.3790e-1 (2.10e-1)	4.9233e-1 (1.53e-1)	5.2321e-1 (3.42e-16)	1.0211e-1 (1.28e-1)	4.8706e-1 (1.11e-1)	3.4341e-3 (4.26e-1)
	250	15	24	250000	3.4151e-2 (1.18e-2)	2.8178e-1 (2.10e-1)	4.8232e-1 (2.53e-1)	5.2321e-1 (3.46e-16)	8.6435e-3 (5.34e-2)	5.10897e-1 (9.76e-2) -	1.1780e-2 (3.58e-1)
	300	20	29	300000	3.4331e-2 (1.40e-2)	6.4101e-2 (8.77e-2)	5.0858e-1 (1.22e-1)	5.2321e-1 (3.50e-16)	4.0133e-2 (1.05e-1)	5.1260e-1 (3.30e-1)	8.7105e-3 (7.03e-2)
					=	-	-	-	-	-	-
DTLZ6	150	5	14	150000	3.2271e-2 (1.09e-2)	4.4617e-1 (9.41e-2)	1.6715e-1 (2.11e-2)	5.2321e-1 (4.42e-16)	1.3882e-2 (1.36e-2)	2.1850e-2 (4.88e-2)	2.0438e-2 (8.01e-2)

	200	10	19	200000	1.7903e-1 (3.42e-1)	4.4257e-1 (6.04e-2)	4.8521e-1 (2.33e-2)	5.2221e-1 (3.56e-14)	1.0541e-1 (8.83e-2)	5.1702e-1 (9.10e-2)		
					-	-	-	-	=	-	5.8004e-1 (2.15e-1)	
	250	15	24	250000	1.1677e-1 (5.08e-1)	4.3847e-1 (8.50e-2)	4.6230e-1 (3.56e-2)	5.2321e-1 (3.68e-16)	1.6826e-1 (8.93e-3)	5.1396e-1 (1.67e-3)		
					-	-	-	-	-	-	6.3630e-1 (3.51e-1)	
	300	20	29	300000	1.9908e-1 (5.86e-2)	4.1526e-1 (9.69e-2)	4.5728e-1 (3.24e-3)	5.2321e-1 (3.52e-16)	1.5637e-1 (1.11e-2)	5.1839e-1 (9.08e-4)		
					-	-	-	-	-	-	2.6315e-2 (3.38e-1)	
DTLZ7	150	5	24	150000	1.7844e-1 (5.87e-2)	1.1550e-1 (7.75e-2)	3.2208e-1 (6.35e-1)			2.6826e-1 (9.92e-3)		
					-	-	-	4.0066e-1 (3.39e-3) -	1.3651e-1 (6.48e-4)	-	1.2905e-1 (2.68e-1)	
	200	10	29	200000	5.8061e-1 (1.25e-1)	8.8838e-1 (4.70e-2)	1.2437e-0 (6.78e-4)			1.2487e-0 (6.79e-3)		
					-	-	-	1.3465e-0 (3.85e-3) -	8.2296e-1 (3.41e-3)	-	4.3144e-1 (2.12e-1)	
	250	15	34	250000	1.3773e-0 (1.27e-1)	1.0059e-0 (3.03e-2)	1.0510e-0 (2.72e-3)			1.0640e-0 (2.39e-3)		
				-	-	-	1.9581e-0 (8.00e-3) -	1.5116e-0 (1.33e-2)	-	3.3850e-1 (1.03e-1)		
	300	20	39	300000	1.8215e-0 (1.26e-1)	1.4544e-0 (2.39e-2)	1.4184e-0 (8.83e-2)			1.4579e-0 (3.96e-3)		
					-	-	-	2.5497e-0 (3.14e-3) -	1.7321e-0 (2.33e-2)	-	8.4732e-1 (1.10e-1)	
DTLZ8	150	5	50	150000					1.3110e-1 (2.06e-2)		2.0338e-1 (5.14e-1)	
									=			
	200	10	100	200000	Non.	Non.	Non.	Non.	7.3560e-1 (2.82e-2)	Non.	3.9309e-1 (4.32e-1)	
									-			
	250	15	150	250000					1.1268e-0 (3.52e-2)		3.8920e-1 (4.55e-1)	
									-			
	300	20	200	300000					1.3177e-0 (2.14e-2)		4.1019e-1 (4.59e-1)	
									-			
DTLZ9	150	5	50	150000			3.1305e-1 (4.01e-3)		3.1436e-1 (4.43e-2)	8.6114e-1 (4.81e-2)	1.8621e-4 (5.23e-4)	
							=		-	-		
	200	10	100	200000		7.7402e-1 (1.56e-2)	1.7126e-0 (6.77e-2)	Non.	3.8665e-1 (4.82e-1)		0	
						-	-		-	-		
	250	15	150	250000	1.0673e-0 (7.76e-3)	8.0136e-1 (1.67e-1)	1.8120e-0 (2.00e-1)		6.4174e-2 (2.67e-1)	1.7372e-2 (4.77e-2)		0
				-	-	-	-		-	=		
300	20	200	300000	3.9400e-1 (3.14e-2)	1.0438e-0 (1.35e-1)	7.9196e-1 (3.33e-1)	3.7680e-3 (3.54e-2)		2.8136e-1 (3.29e-1)		0	
					-	-	-	=	-			
+/-/=					0/27/3	0/30/1	0/29/3	0/27/1	0/30/6	0/28/3		

CONVERGENCE GRAPHS

Once again, an asymptotic graph was drawn for both data sets to illustrate how the estimated values converged with increasing cycles. All data were subjected to 100,000 iterations. Below are some visual representations of the mechanical and conceptual efficacy of the suggested algorithm in rapidly reaching the ideal end product. So, MOEA/D, MOPSO, NSGAI, and SPEA2 were the compared algorithms. Graphs for all seven methods have been generated and obtained after 100,000 iterations of Hyper Volume (HV) and IGD, respectively. Figures (1) and (2) display the outcomes:

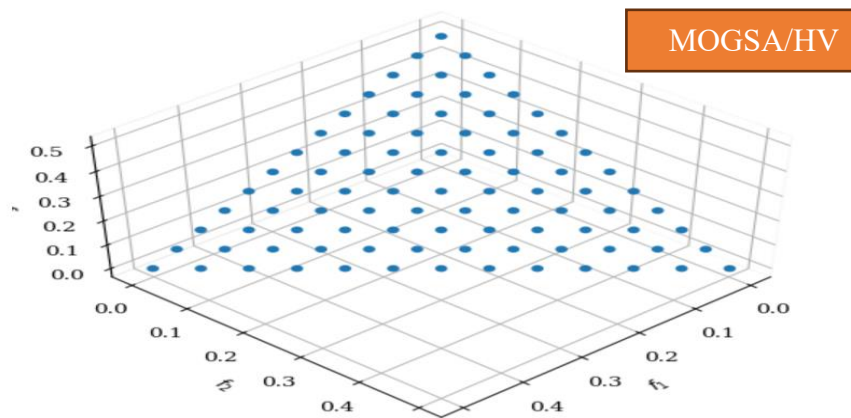


FIGURE 1: A suitability value graph for DTLZ1

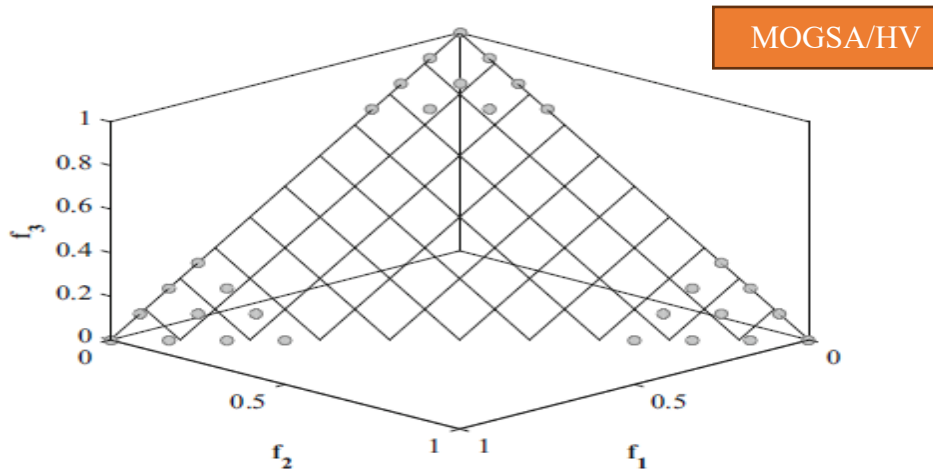


FIGURE 2: A suitability value graph for DTLZ2

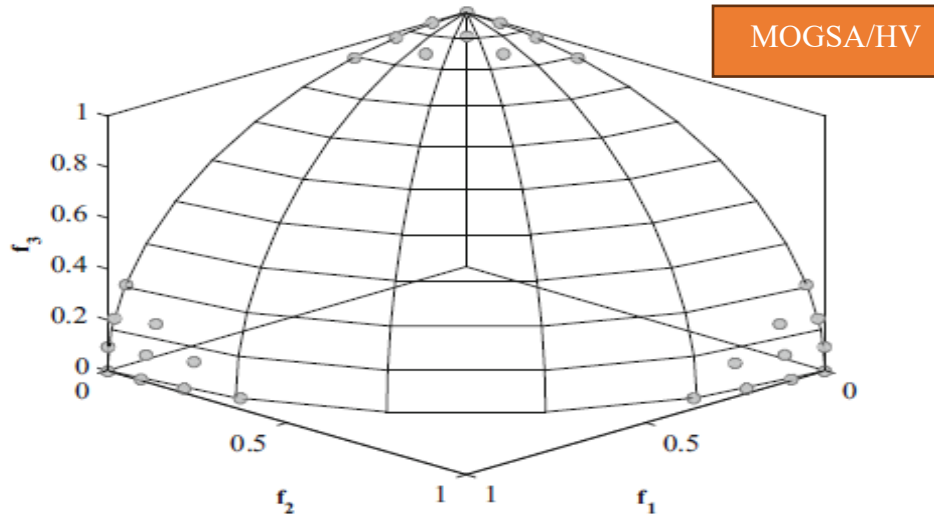


FIGURE 3: A suitability value graph for DTLZ3

The suggested approach finds an equilibrium point more quickly, as seen in the diagrams for figures 1, 2, and 3. Though the MOGSA/HV and MODEMR algorithms produce fast end products, the latter yields a superior value.

CONCLUSIONS

In the present study, we provide several objectives for GSA that depend on degradation subsystems (MOGSA/HV). These strategies break down MOPs into numerous scalar enhancement sub-issues, and in one iteration, each sub-issue is improved by leveraging knowledge from its own few neighboring sub-issues. The IGD and HV performance indicators show that MOGSA/HV is an efficient algorithm that surpasses the selected MOBATs. The quantity of Pareto battles indicates that MOGSA/HV may provide excellent Pareto lines, especially when compared with previously selected MOBATs.

We do further evaluations and testing on the suggested. Statistical analyses for various test issues, such as discrete and blended improvement objectives, will be our primary emphasis later in this assignment. We aim to determine how to improve this calculation for different problems by looking at the Pareto frontlines it may create. Several efficient methods exist for generating different Pareto fronts; by integrating these methods alongside others, MOGSA/HV might be significantly enhanced.

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