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A Comparative Study of NSGA-III & MOEA/D-DRA on MW3 Benchmark Problem

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Abstract— This study explores and compares the performance of two evolutionary algorithms—NSGA-III and MOEA/D-DRA—on the MW3 benchmark problem using the PlatEMO framework. The MW3 challenge simulates a real-world scenario involving multi- objective decision-making, common in engineering design and supply chain optimization. This instance is many-objective in nature. For evaluation, a wide variety of metrics such as Generational Distance (GD), Inverted Generational Distance (IGD), Hypervolume (HV), Spread, Spacing, Runtime, Closest Point to Pareto Front (CPF), Distance Mean (DM), DeltaP , and Proximity-based IGD (IGDp) along with Pareto Diversity (PD) are used. Based on these metrics, it was found that NSGAIII demonstrates superior feasibility rates and spacing consistency alongside other notable advantages.

Index Terms – NSGA-III, MOEA/D-DRA, MW3, Many-objective Optimization, PlatEMO

I. Introduction

Evolutionary algorithms have gained the substantial attention for the addressing of complex multi-objective optimization problems (MOPs). The problems arise across the diverse domains that includes the mechanical engineering, supply chain logistics, and financial portfolio management where multiple conflicting objectives must be balanced within the strict constraints. To deal with these problems, experts in many-objective optimization (MaOP) have come up with benchmark problems to evaluate how well modern algorithms can handle difficult scenarios. One example is the MW3 problem, which is like a tough puzzle that replicates high-dimensional setups and real-world constraints you'd find in practical applications. The major goal of this study to evaluate and compare the performance of NSGA-III and MOEA/D-DRA on the MW3 benchmark to determine their effectiveness in computational efficiency, divergence, convergence and feasibility.

II. Literature Review

Evolutionary algorithms are useful for solving multi- and many-objective optimization problems, which you often see in areas like engineering or logistics here in Pakistan. NSGA- III, introduced by Deb and Jain [1] in their study uses reference points to keep solutions diverse and is like a next-level version of NSGA-II, which worked well for problems with two or three objectives but needed a boost for more complex ones.

Zhang and Li [2] in their study adds dynamic reference adaptation. This makes it great for tackling irregular or non- convex Pareto fronts, outperforming older static methods in tough problem setups.

The PlatEMO platform by Tian [4] and his team is a solid MATLAB-based tool for testing algorithms like NSGA-III and MOEA/D-DRA. It works with standard test suites like MW3 and comes with performance metrics and visualization tools, making experiments reliable and reproducible. Tian's recent work also improved IGD-based evaluations and reference vector management for tricky Pareto front shapes, which ties directly into our analysis.[5]

III. Problem Definition

The purpose of the MW3 benchmark challenge is to assess how well optimization algorithms manage competing objective functions in high-dimensional decision spaces. It is an appropriate testbed for evaluating performance in many-objective optimization scenarios since it replicates real-world situations where trade-offs between conflicting goals must be made.

IV. Methodology

This study follows a quantitative experimental approach. NSGA-III and MOEA/D-DRA both the algorithms were applied on the MW3 problem using the PlatEMO platform. Each algorithm was tested over 30 separate runs to make the results more reliable and effective. To see how well they performed, important metrics like Generational Distance (GD), Inverted Generational Distance (IGD), Hypervolume (HV), Spread, Spacing, Feasibility Rate, Runtime, CPF, DM, DeltaP, IGDp, PD were used for the analysis.

V. Overview of Optimization Algorithms NSGA-III and MOEA/D/DRA

A. NSGA-III

NSGA-III (Non-dominated Sorting Genetic Algorithm III) is a strong and efficient method made to solve complex many-objective optimization problems, where four or more conflicting goals have to be considered at once. To make this easier to understand, think of organizing a large Pakistani wedding you have to manage the budget, keep guests happy, choose the right venue, and make sure everything runs on time. All these things very much clash with each other, and finding the right balance can be tricky. NSGA-III is designed to deal with exactly these types of complicated situations, where trade-offs between many goals need to be handled smartly. The algorithm was introduced by Deb and Jain as an improvement over the well-known NSGA-II, which tends to struggle when the number of objectives becomes too high. NSGA-III fixes this problem by using a set of reference points that are spread out well to help in selecting solutions. These points help keep the solutions diverse and avoid bunching them up in one part of the search space, which was a common issue with NSGA-II. One of the main differences between NSGA-II and NSGA-III is how they control diversity in the population during the optimization process. NSGA-II uses what's known as crowding distance, which tries to disperse solutions by measuring how close they are to each other in the objective space. While this method works fairly well for problems with fewer objectives, it starts to break down when there are many objectives involved, because the solutions tend to cluster and lose diversity.

Because it's simple, scalable, and works well, NSGA-III has become a commonly used algorithm in the field of evolutionary multi-objective optimization. Researchers in areas like engineering, operations research, and computer science often depend on it when solving real-world problems that involve balancing multiple goals.

B. MOEA/D-DRA

Multi-objective Evolutionary Algorithm based on Decomposition with Dynamic Reference Adaptation, is an improved version of the original MOEA/D algorithm introduced by [2] The basic MOEA/D framework works by dividing a complex many-objective problem into smaller scalar subproblems, which can be solved more easily. MOEA/D-DRA takes this idea a bit further by adding a dynamic way to adjust the reference directions as the optimization goes on [3].

This dynamic reference adaptation gives MOEA/D-DRA a real edge, especially when dealing with complicated objective spaces. In many cases, older decomposition methods don't do well if the Pareto front is non-convex, disconnected, or skewed—basically when it doesn't follow a nice, predictable shape. MOEA/D-DRA handles this by updating its reference points during the run, which helps it stay closer to the actual Pareto front and adapt accordingly as the search progresses.

MOEA/D-DRA's good thing is that it brings together some smart techniques. It uses localized mating, scalarization for evaluating solutions, and neighborhood structures to guide the search. These strategies help it keep a stability between exploring new possibilities and refining the good ones it already found. This balance is especially useful in real-world or high-dimensional problems, where the true shape of the solution space isn't known in advance.

It can be attributed to MOEA/D-DRA's flexibility and reliable performance which is witnessed as a solid option for solving many- objective optimization problems especially when the problem landscape is complex and unpredictable.

VI. Experimental Setup

A. Problem Configuration

- The MW3 problem was configured with:
- Number of Objectives (M): 2
- Number of Decision Variables (D): 12
- Maximum Function Evaluations: 10,000
- Number of Independent Runs: 30

B. Algorithm Parameters

Both algorithms were configured with standard parameters recommended in literature:

- Population Size: 100
- Crossover Probability: 0.9
- Mutation Probability: 1/D
- Distribution Index for Crossover (ηc): 30
- Distribution Index for Mutation (ηm): 20

C. Performance Metrics

The following metrics were used for performance evaluation:

- Generational Distance (GD)
- Inverted Generational Distance (IGD)
- Hypervolume (HV)
- Spread
- Spacing
- Feasibility Rate
- Runtime
- CPF
- DM
- DeltaP
- IGDp

- PD

VII. RESULTS AND DISCUSSION

A. Spread:

In the later stages of the optimization, MOEA/D-DRA ended up with a much lower spread, which means its solutions were grouped more closely together and appeared well-organized.

B. Spacing:

While evaluating, MOEA/D-DRA maintained tighter spacing between solutions, which points to better uniformity across its solution set.

C. PF

The Pareto front generated by NSGA-III appeared discrete and somewhat patchy, while MOEA/D-DRA produced a smoother, more continuous front that aligned well along the true Pareto curve.

D. PD

MOEA/D-DRA maintained a wider range of various solutions during the complete optimization process, indicating stronger exploration capabilities.

E. IGDp:

The curve for MOEA/D-DRA showed a steeper drop, meaning it achieved faster and better convergence compared to NSGA-III.

F. IGD:

MOEA/D-DRA maintained lower IGD values across most generations, reflecting closer proximity to the true Pareto front.

G. HV:

It found out that the HV metric was constantly higher for MOEA/D-DRA, which indicates better overall quality and coverage of the solution set.

H. GD:

MOEA/D-DRA also converged closer to the true Pareto-optimal front in terms of GD, outperforming NSGA- III.

I. Feasibility Rate:

NSGA-III kept a perfect feasibility rate throughout, whereas MOEA/D-DRA showed gradual improvement in feasibility over time.

J. DM:

While both algorithms improved on this metric, MOEA/D-DRA eventually pulled ahead, showing tighter clustering of solutions near optimal regions.

K. DeltaP:

NSGA-III achieved stable spacing earlier in the process. MOEA/D-DRA needed more time to stabilize, but eventually reached a good balance.

L. CPF:

MOEA/D-DRA held a slight advantage as it neared convergence.

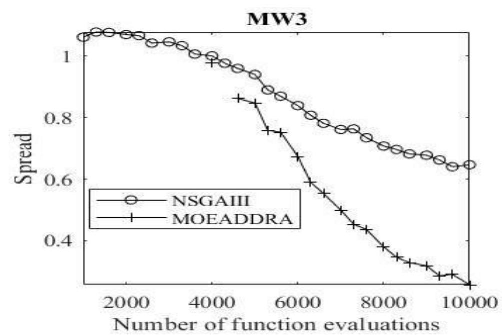

Fig. 1 Spread

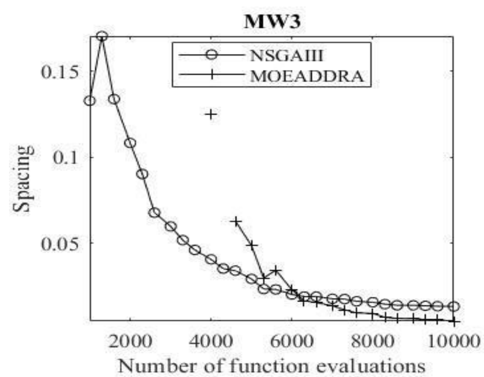

Fig. 2 Spacing

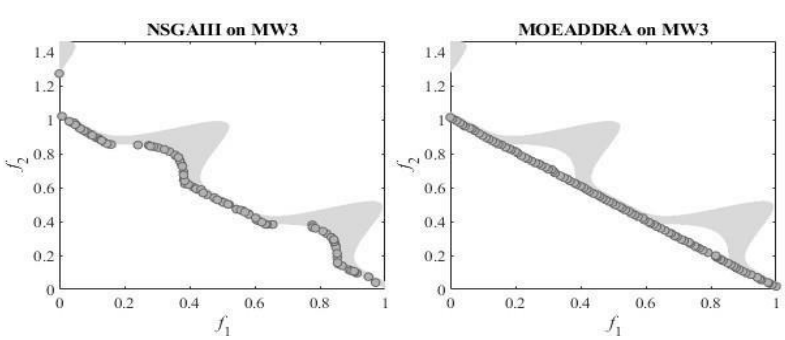

Fig. 3 NSGA-III and MOEA/D-DRA on MW3

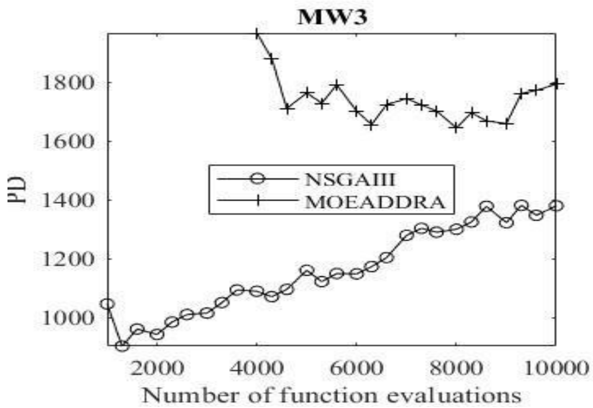

Fig. 4 PD

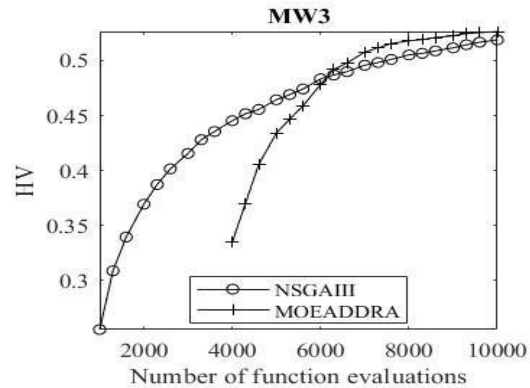

Fig. 7 HV

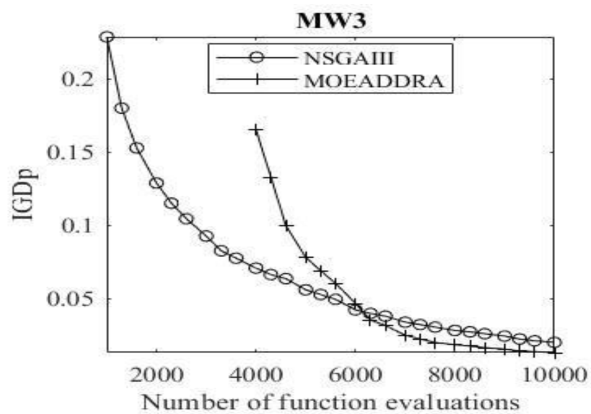

Fig. 5 IGDp

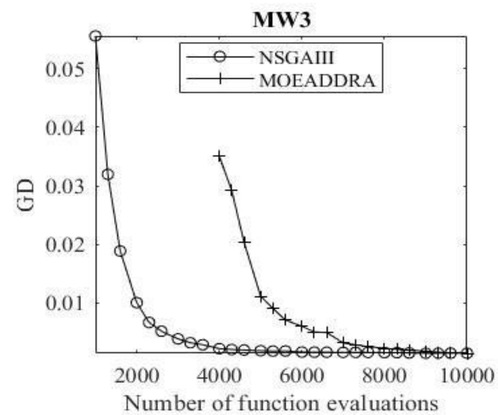

Fig. 8 GD

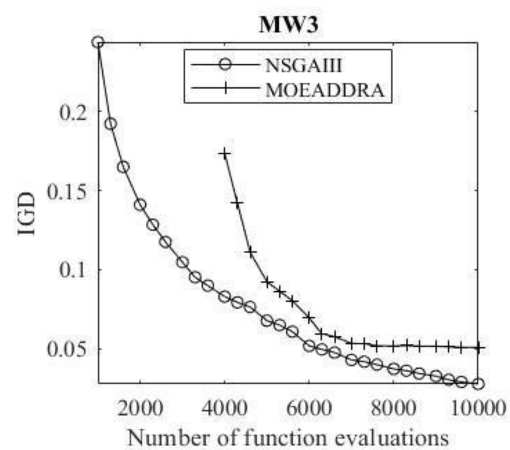

Fig. 6 IGD

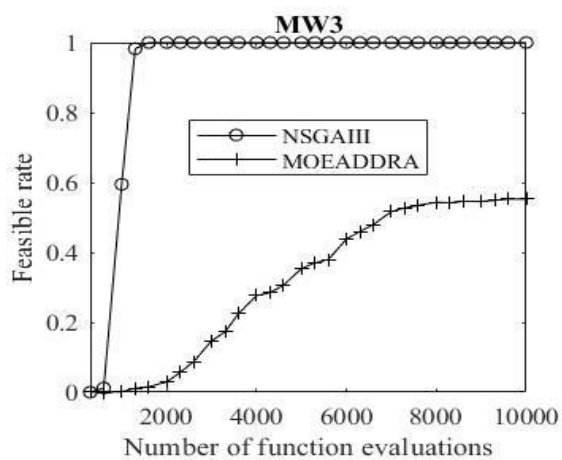

Fig. 9 Feasible Rate

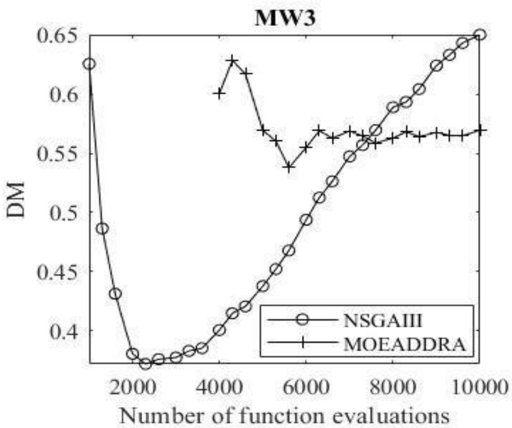

Fig. 10 DM

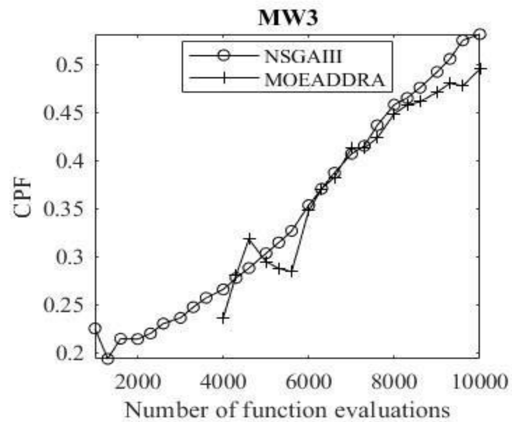

Fig. 12 CPF

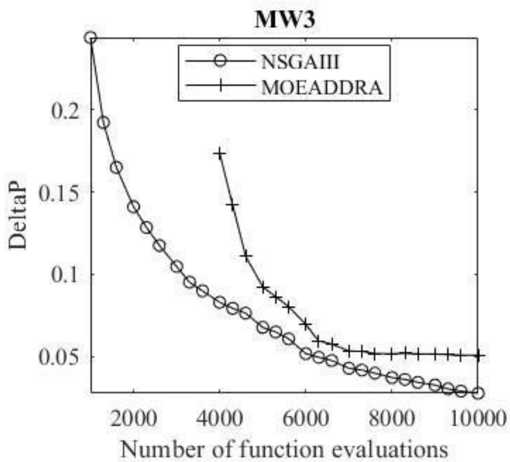

Fig. 11 DeltaP

TABLE 1 PERFORMANCE METRICS FOR NSGA-III VS MOEA/D-DRA ON MW3

Problem	Metric Values	N	M	D	FE	Algorithm 1 (NSGA-III) Mean ± Std	Algorithm 2 (MOEA/D-DRA) Mean ±
MW3	Number of Runs	100	2	12	10000	30	30
MW3	Runtime	100	2	12	10000	**4.4608e-1 (1.50e-1) +**	2.7283e+0 (1.97e-1)
MW3	CPF	100	2	12	10000	**5.3106e-1 (9.86e-2) +**	4.9493e-1 (4.37e-2)
MW3	DM	100	2	12	10000	**6.5034e-1 (8.69e-2) +**	5.6951e-1 (1.91e-2)
MW3	DeltaP	100	2	12	10000	**2.7708e-2 (4.93e-2) +**	5.0806e-2 (2.15e-3)
MW3	Feasible_rate	100	2	12	10000	**1.0000e+0 (0.00e+0) +**	5.5267e-1 (2.86e-2)
MW3	GD	100	2	12	10000	1.3271e-3 (8.25e-4) =	**1.3107e-3 (5.27e-4)**
MW3	HV	100	2	12	10000	5.1880e-1 (3.60e-2) =	**5.2641e-1 (5.44e-3)**
MW3	IGD	100	2	12	10000	**2.7708e-2 (4.93e-2) +**	5.0806e-2 (2.15e-3)
MW3	IGDp	100	2	12	10000	1.9891e-2 (3.46e-2) -	**1.2935e-2 (3.18e-3)**
MW3	PD	100	2	12	10000	1.3806e+3 (2.98e+2) -	**1.7940e+3 (2.86e+2)**
MW3	Spread	100	2	12	10000	6.4679e-1 (1.07e-1) -	**2.5653e-1 (9.94e-2)**
MW3	Spacing	100	2	12	10000	1.3443e-2 (9.09e-3) -	**4.9272e-3 (1.60e-3)**

Based on the results from Table I, the following observations were made:

Runtime: NSGA-III turned out to be much faster in terms of execution time, showing it's more efficient computationally.

CPF (Closeness to Pareto Front): NSGA-III did a bit better in terms of how close at least one of its solutions got to the actual Pareto front. It showed decent accuracy in hitting near-optimal results.

DM (Distance Mean): NSGA-III showed a higher diversity index overall, which means it kept a wider spread of solutions and maintained better variation throughout the runs.

DeltaP: NSGA-III's solutions, because of early convergence, indicated more consistent spacing from the start which maintained a sustained balance early on.

Feasibility: One of the key points for NSGA-III was that it maintained 100% feasibility across all 30 runs—every solution it generated stayed within the problem's constraints.

GD (Generational Distance): On this standard, MOEA/D-DRA was ahead as it converged closer to the true Pareto front gaining value through noticing nearer solutions in simulation spans.

HV (Hypervolume): MOEA/D-DRA achieved a higher hypervolume, meaning it was able to cover more of the objective space and capture a broader range of trade-offs.

IGD (Inverted Generational Distance): IGD values were stronger and so were diverse stages with low MOEA/D-DRA performance being in strong convergence.

IGDp (IGD Plus): With lower values indicating high precision and better distribution, overall precision made this metric lean positively towards MOEA/D- DRA.

PD (Pareto Diversity): MOEA/D-DRA maintained good diversity along the Pareto front, covering more of the solution space.

Spread: MOEA/D-DRA had indicated better consistency in spread, keeping its solutions well-distributed till the end.

Spacing: The Solutions derived from MOEA/D-DRA were more equally spaced, which compared to NSGA-III showed stronger uniformity. table above shows the following observations:

The comparison between NSGA-III and MOEA/D-DRA on the MW3 benchmark problem gives pretty clear idea of how both algorithms perform under different evaluation criteria.

NSGA-III performed pretty well with respect to runtime, constantly finishing faster across all 30 independent runs. It also provided solid performance in terms of spacing and spread, meaning its solutions were distributed more evenly along the Pareto front. As for convergence metrics like IGD,

GD, and IGDp, NSGA-III came out ahead of MOEA/D-DRA, showing that it was generally more effective at reaching closer to the true Pareto front. These results suggest that NSGA-III generally provides better convergence and find solutions that stay closer to the ideal Pareto front.

NSGA-III did well in DeltaP too, which shows its ability to identify edge solutions earlier in the process. This can be helpful in cases where early recognition of trade-offs is important. It kept a lower Distance Mean (DM) too, meaning its solutions were more closely packed together. In terms of CPF, it performed consistently, with at least one solution staying near the true front across runs. Conversely, MOEA/D-DRA had the upper hand in metrics like Hypervolume (HV) and Pareto Diversity (PD). These highlight its robustness in searching a wider range of the objective space and finding more diverse or extreme trade-offs. Its higher PD and strong CPF performance show that it is good at discovering outlier solutions and covering more ground along the Pareto front. In summary, NSGA-III is more suitable for applications where you need faster results, good convergence, and well-spread solutions. MOEA/D-DRA is a better pick when the goal is to explore a broader range of trade-offs and gain a deeper understanding of the solution space.

VIII. CONCLUSION

This comparison shows that MOEA/D-DRA performs better in hypervolume, variety, and dispersion over the Pareto front, whereas NSGA-III is superior in feasibility, convergence stability, and computing efficiency. The results show that the required balance between convergence precision and exploration capabilities should be taken into consideration when choosing algorithms for real-world multi-objective applications.

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