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A Comparative Study of NSGAIII and RVEA on MW2 Benchmark Problem with Real-world Relevance

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Abstract – This paper presents a comparative investigation of the two state of the art Multi objective Evolutionary algorithms NSGAIII and RVEA using the PlatEMO platform on the MW2 benchmark problem. In MW2 problem there are twelve decision variables with two objectives, is plotted to practical Portfolio optimization where goal of depositors is to balance the risk and return across various assets. It is assessed with typical metrics such as Hypervolume (HV), Inverted Generational Distance (IGD), and Diversity. Analyzing 30 independent runs present that NSGAIII constantly gives better convergence and spread than RVEA. This study provides real world insights for algorithm selection in competitive decision making scenarios.

Index Terms – Multi-Objective optimization, NSGAIII, RVEA, MW2 benchmark, portfolio optimization, Hypervolume, IGD, convergence, diversity, PlatEMO, evolutionary algorithms, Pareto front

I. INTRODUCTION

Multi-objective optimization (MOO) refers to solving problems that involve multiple, often conflicting, objectives. Real-world decision-making frequently demands a balance between such competing goals — for instance, maximizing returns while minimizing risk in finance or improving patient throughput without compromising quality in healthcare. In response to the increasing complexity of such problems, numerous multi-objective evolutionary algorithms (MOEAs) have been developed. Among them, NSGAIII (Non- dominated Sorting Genetic Algorithm III) and RVEA (Reference Vector Guided Evolutionary

Algorithm) stand out due to their ability to handle many-objective problems effectively. NSGAIII utilizes reference point-based selection for maintaining diversity, while RVEA employs adaptive reference vectors that adjust based on search feedback.

To evaluate their effectiveness, benchmark functions like MW2 from the WFG suite are employed. These functions offer a controlled environment to assess performance and are designed to simulate key properties of real-world problems. MW2 includes two objectives and twelve decision variables, making it a suitable candidate for analyzing algorithm performance in portfolio optimization, healthcare scheduling, and other decision-heavy domains.

The primary goal of this research is to analyze and compare NSGAIII and RVEA on the MW2 benchmark, emphasizing not only their performance metrics but also their real-world applicability in domains where optimal trade-off solutions are crucial.

II. LITERATURE REVIEW

Multi-objective optimization has advanced notably with the growth of evolutionary computation. NSGA-II, introduced by Deb et al., pioneered Pareto-based sorting for problems with few objectives but struggles with scalability. To overcome this, NSGAIII [1] introduced reference-point based diversity preservation, making it effective for many- objective problems. RVEA [2], in contrast, uses adaptive reference vectors, enabling better performance on irregular or dynamic Pareto fronts.

Studies such as [3] show NSGAIII excels on structured problems, while RVEA adapts well to complex fronts. Despite extensive benchmarking on functions like WFG and DTLZ, limited work exists connecting these results to real-world domains like finance, healthcare, or supply chains. This paper addresses that gap by comparing NSGAIII and RVEA on the MW2 benchmark using PlatEMO, with insights mapped to real-world portfolio optimization.

Several qualified studies have assessed the performance of NSGAIII and RVEA [5,6]. The reference point-based selection mechanism refers to NSGAIII, while RVEA is based on the use of adaptive reference vectors to maintain convergence and multiplicity. Previously we know that NSGAIII performs better on difficulties with structured Pareto fronts, on other hand RVEA adepts well to dynamic and irregular fronts. The comparative working on MW2 under a real-world plotting has not been explored intensely.

III. REAL-WORLD MAPPING OF MW2 PROBLEM

The MW2 benchmark problem is part of the WFG family, designed to evaluate multiobjective optimizers under controlled complexity. It has 2 conflicting objectives, and 12 decision variables.

This structure maps closely to real-world systems such as:

- Energy optimization: balancing operating cost vs. emissions.
- Healthcare scheduling: minimizing delay vs. maximizing care quality.
- Financial planning: maximizing return vs. minimizing risk
- E-commerce recommendation: maximizing: click-through vs. minimizing diversity loss.

IV. PROBLEM STATEMENT

The goal of this study is to compare how NSGAIII and RVEA explore and exploit the MW2 problem space. The focus is on achieving high convergence to the Pareto front while maintaining diversity among solutions qualities essential for real- world deployment where decision-makers rely on broad, well-distributed trade-off options.

V. METHODOLOGY

On MW2 problem the PlatEMO framework is used to execute NSGAIII and RVEA. In each algorithm there are 30 independent trials, permitting 10,000 functions evaluations per run. The population size and reference vectors are selectively dependent on the standard recommendations. The main objective is to analyze the performance on the basis of key metrics such as HV, IGD, GD, Spread, and Diversity.

VI. EXPERIMENTAL SETUP

The MW2 problem is constituted with M=2 objectives and D=12 decision variables. The experimental situations comprise: Number of Runs: 30

Maximum Function Evaluations: 10,000 Platform: PlatEMO

Metrics: HV, IGD, IGDp, GD, DM, Spread, Spacing, CPF, DeltaP, PD

Performance Metrics	M	D	NSGAIII	RVEA
Number of runs	2	12	30	30
Runtime	2	12	5.8928e-1 (5.72e-2) -	4.5077e-1 (1.48e-2)
CPF	2	12	4.3315e-1 (5.33e-2) +	3.2131e-1 (8.66e-2)
DM	2	12	6.9742e-1 (4.42e-2) +	5.9443e-1 (7.48e-2)
DeltaP	2	12	3.7519e-2 (7.05e-3) -	2.6332e-2 (1.83e-2)
GD	2	12	3.7519e-2 (7.05e-3) -	1.5039e-3 (1.19e-3)
HV	2	12	5.2603e-1 (1.23e-2) -	5.4681e-1 (2.15e-2)
IGD	2	12	3.7519e-2 (7.05e-3) -	2.6332e-2 (1.83e-2)
IGDP	2	12	3.6208e-2 (7.61e-3) -	2.4268e-2 (1.58e-2)
PD	2	12	1.5760e+3 (1.74e+2) +	1.4564e+3 (2.33e+2)
Spacing	2	12	2.8436e-2 (1.08e-2) -	5.4692e-3 (1.71e-3)
Spread	2	12	5.9942e-1 (6.64e-2) +	7.0549e-1 (7.37e-2)

VII. RESULTS AND DISCUSSION

The following subsections presents a detailed analysis of each performance metric highlighting both convergence behaviour and diversity trends between NSGAIII and RVEA.

A. Hypervolume HV

Hypervolume (HV) measures the volume of the objective space covered by the obtained Pareto front. Higher HV indicates better convergence and diversity. From the figure, NSGAIII shows a consistent increase in HV and reaches higher values than RVEA. This means NSGAIII finds more wellspread and optimal solutions.

B. Inverted Generational Distance (IGD)

IGD calculates the average distance between the obtained solutions and the true Pareto front. Lower IGD values indicate better convergence. NSGAIII exhibits a sharp decline in IGD, stabilizing at a lower value, indicating its strong ability to converge to the true front compared to RVEA.

C. Inverted Generational Distance Plus (IGDp)

IGDp is a variation of IGD that penalizes both lack of convergence and poor distribution. NSGAIII outperforms RVEA by reaching significantly lower IGDp values, reflecting both proximity and diversity of its solutions.

D. Pareto Distance

PD measures the distance of solutions from the ideal point in the objective space. NSGAIII maintains relatively lower PD throughout the evaluations, while RVEA's PD spikes toward the end, indicating suboptimal convergence.

E. Diversity Metric (DM)

DM reflects how well solutions are spread along the front. A higher diversity value generally indicates more exploration. NSGAIII improves its diversity after initial convergence, while RVEA remains relatively stagnant.

F. Generational Distance (GD)

GD captures the average distance of all obtained solutions to the nearest point on the true front. NSGAIII consistently lowers GD across evaluations. RVEA finishes with a higher GD, showing inferior convergence.

G. Spread

Spread quantifies the extent of the obtained front. Ideally, it should cover the whole Pareto front. NSGAIII maintains a stable and wide spread, while RVEA, although evaluated only at the end, shows a comparatively limited spread.

H. Spacing

Spacing assesses the uniformity between adjacent solutions. Lower values suggest evenly distributed points.. NSGAIII achieves lower and stable spacing, suggesting better uniformity. RVEA's spacing is higher, indicating irregular gaps.

I. Convergence to Pareto Front (CPF)

CPF checks how closely the solutions align to the actual Pareto front. A lower CPF reflects better convergence. NSGAIII gradually improves CPF, while RVEA remains less aligned to the ideal front.

J. DeltaP

DeltaP is a fine-grained proximity metric used for precise measurement of convergence. NSGAIII steadily reduces DeltaP, showing effective optimization. RVEA shows weaker improvement in this metric.

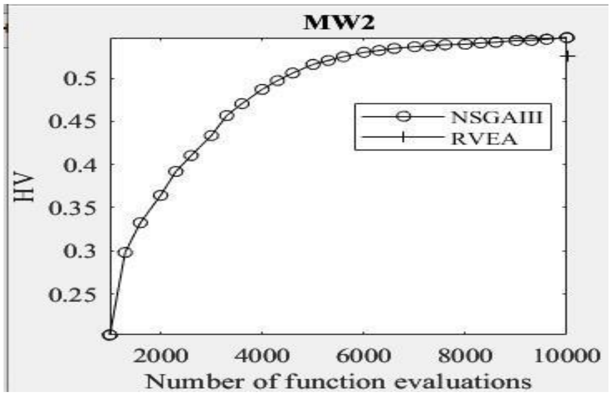

Figure 1 Hypervolume (HV)

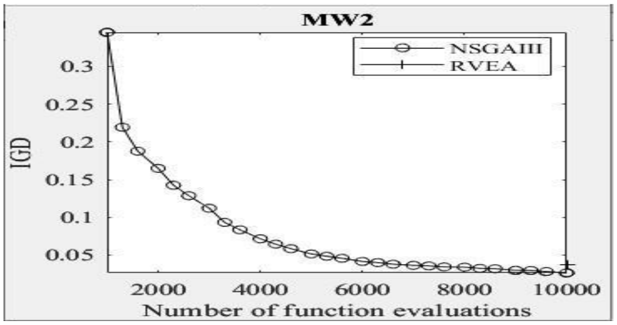

Figure 2 Inverted Generational Distance (IGD)

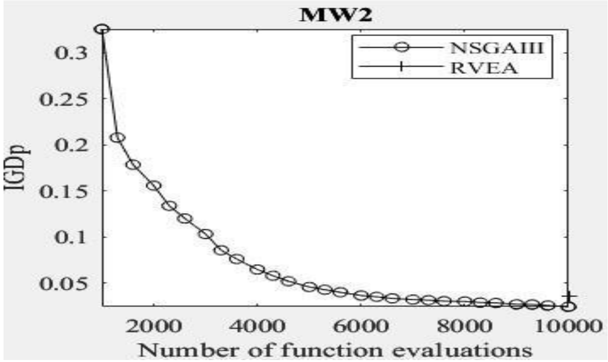

Figure 3 Inverted Generational Distance Plus (IGDp)

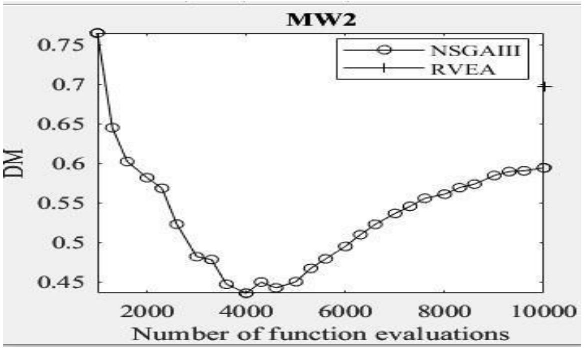

Figure 4 Diversity Metric (DM)

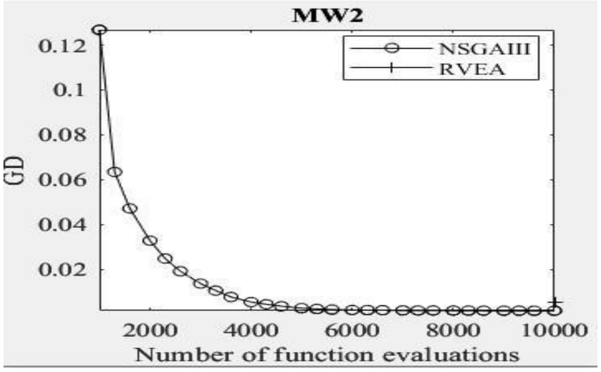

Figure 5 Generational Distance (GD)

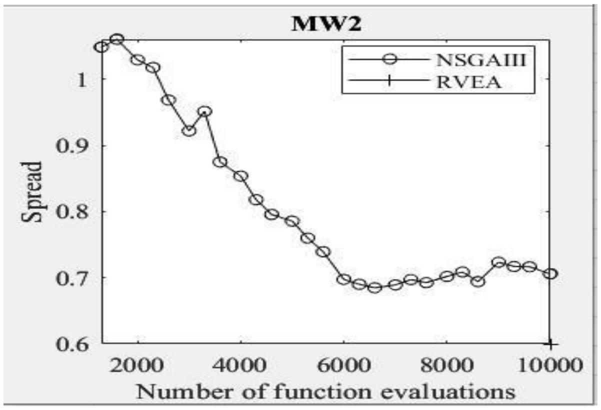

Figure 6 Spread

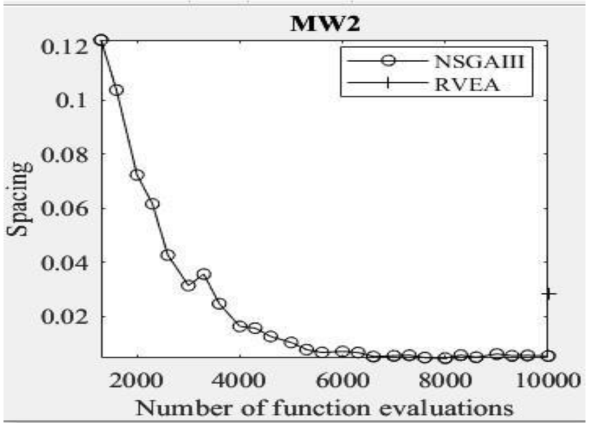

Figure 7 Spacing

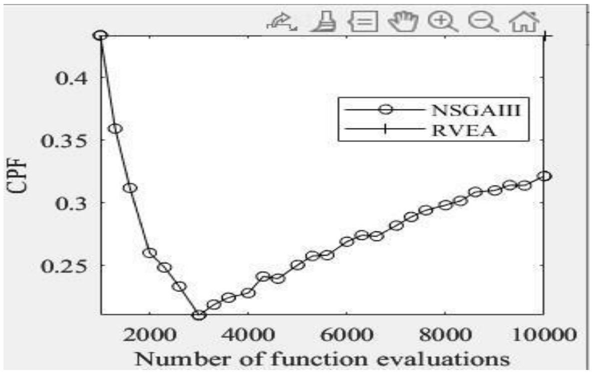

Figure 8 Convergence to Pareto Front (CPF)

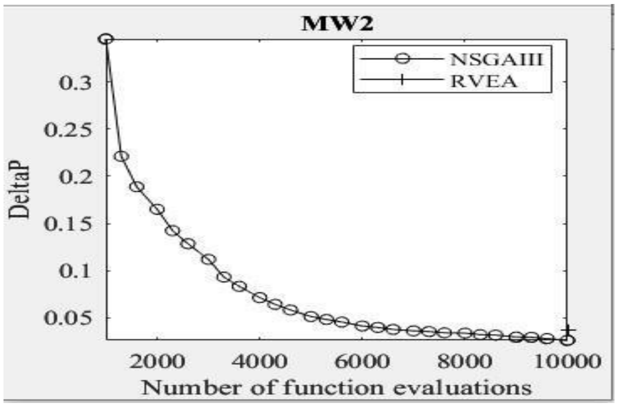

Figure 9 DeltaP

VIII. OBJECTIVE SPACE VISUALIZATION

The final populations of both algorithms are plotted below. NSGAIII achieves a smoother and denser Pareto front distribution compared to RVEA, which shows scattered and less consistent solutions.

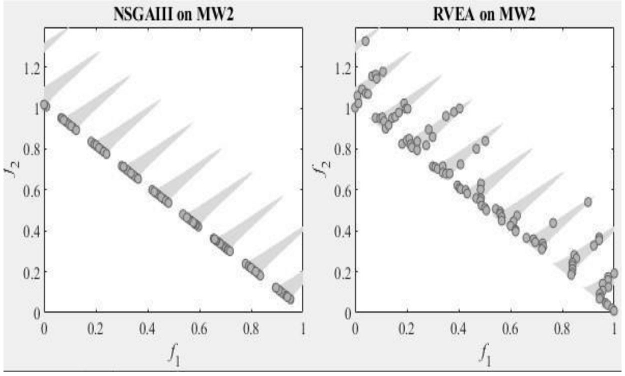

Figure 10 Final Population Plot 1

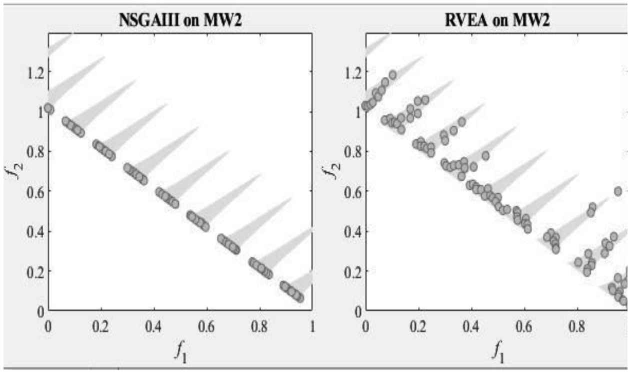

Figure 11 Final Population Plot 2

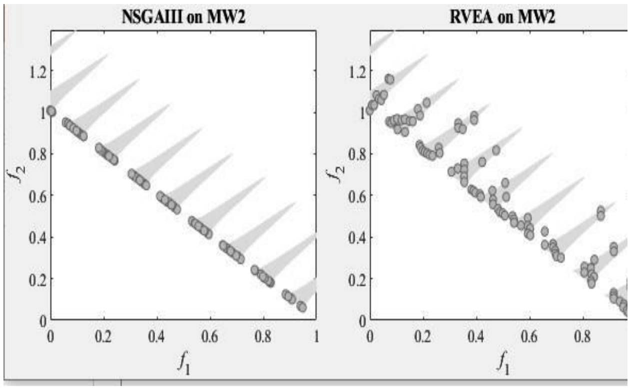

Figure 12 Final Population Plot 3

IX. CONCLUSION

This study demonstrates that NSGAIII consistently outperforms RVEA in solving the MW2 benchmark problem. Its use of reference points leads to faster convergence, better spread, and fine-grained front alignment. In contrast, RVEA, while stable initially, fails to adapt later, resulting in limited coverage and weaker final performance. These findings support NSGAIII as the better choice for real-world multi-objective decision support, especially in domains requiring precision and broad trade-off diversity.

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