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Benchmarking Modern Evolutionary Algorithms for Multi-Modal Multi-Objective Optimization: A Comprehensive Performance Matrix Analysis

Muhammad Waqar Khan [1] *, Adnan Ahmed Siddiqui [1], Syed Sajjad Hussain Rizvi [2]
Faculty of Engineering Science and Technology, Hamdard University, Karachi, Pakistan
Faculty of Computing and Engineering Sciences, SZABIST University, Karachi, Pakistan

Corresponding author: mwaqarkhan320@gmail.com

Abstract:

The Multi-modal Multi-Objective Optimization (MMO) paradigm has received greater attention because of its applicability and affinity for mapping problems. Multi-objective problems can be solved by classical evolutionary algorithms (EAs), which are ideal candidates for such complex problems. However, these EAs are deficient in addressing issues related to multi-modal functions. Likewise, modern EAs have been shown to solve various benchmark functions and optimization problems. But, the extent of analysing its performance comprehensively on today's complex EAs is remarkably scarce in the literature regarding the proposal of the MMO function. This study conducts an extensive analysis of modern EAs on benchmark MMO functions (six functions and three EA algorithms). These include spacing, spread, distance, diversity, convergence, and the run-time identified properties. The properties are then linked with the twelve performance metrics. This work also introduced the optimal EA for managing the MMO benchmark function. The empirical evidence used in the proposed framework is the performance matrix to select the best EA for the function of MMO.

Keywords: *Multi-modal Multi-objective Optimization, Evolutionary Algorithm, solution diversity, convergence, distance, time, Pareto Optimal Solutions, Benchmark Problems, Objective Vectors, Optimization Framework*

I. INTRODUCTION

The MMOs have attracted interest in the last few years. They are helpful and applicable to solving optimization problems in real-life contexts. Some of these domains, including Supply Chain Management [1], Portfolio Optimization [2], Energy Systems Optimization [3], Engineering Design, and Drug Discovery [4], are others. In these domains, the nature of problems is complex, as decision-makers are faced with several objectives most of the time, and these objectives may possess more than one optimum solution. This characteristic is inconvenient regarding classical optimisation techniques, which can be applied if the function is more comprehensible [5]. This poses a significant challenge in developing a state-of-the-art EA that could solve MMO problems [6]. It is important to note that the EAs have evolved into one of the powerful categories of optimisation methods that can efficiently solve MMO problems. Nevertheless, it may require more sophisticated forms when working on multi-modal functions, in which case the aim will be to identify multiple global optima for each work [7]. In addition, the quantitative comparisons of most modern EAs on the performance of the corresponding MMO problems still need to be made available in the present literature. This gap is essential for analysing the modern EAs on the benchmark MMO functions, emphasising the fundamental properties of spacing, spread, distance, diversity, convergence, and the run-time identified properties [8]. The properties are then linked with the twelve-performance metrics for comparative analysis [9]. In the domain of evolutionary computation, several novel and advanced methods have been proposed to solve complex optimization problems. The Constrained Multi-Objective Optimization based on the Evolutionary Multitasking Optimization (CMOEMT) algorithm leverages the concept of multitasking to solve multiple objective problems that have constraints in improving the efficiency of solving the different tasks as knowledge is shared across the tasks [10]. On the other hand, the Large-scale Evolutionary Algorithm with Reformulated Decision Variable Analysis theme (LERD) deals with large-scale optimization problems by reformulating the decision variables to increase the convergence rate and reduce the size of the problem [11]. This approach is more helpful when many search dimensions are needed to solve the problem. Furthermore, the Multi-Population Coevolutionary Constrained Multi-objective Optimization (MCCMO) algorithm proposed integrating a coevolutionary strategy with more than one population to help search for various areas in the objective space [12]. Thus, the MCCMO improves the ability to seek the best solutions within the constraints not only for distinct sub-populations but also for two sub-populations, such as competitors and cooperants. Altogether, these algorithms incorporate essential advances in the approach to evolutionary computation, and each of them provides methodologies that are different from the others to overcome the existing difficulties in confronting constrained multi-objective optimization [13]. This study is an attempt to fill this research gap by providing an extensive comparison of existing state-of-the-art EAs on benchmark MMO functions. This will help in understanding the efficiency and inefficiency of various EAs for MMO problems and develop a unified criterion for selecting the most appropriate EA for MMO problems. Using data from performance metrics, this study aims to advance knowledge of how best to apply modern EAs to solve various MMO problems and ultimately benefit the optimisation field.

II. PRACTICAL IMPLEMENTATION

The applicability of MMMO is extended directly to several real-world decision and engineering support domains. In this regard, the planning and optimization of the Hybrid Renewable Energy System is a notable example in which there is a collaborative optimization of the emission levels, storage designs and the cost reliability. Since the different combinations of the wind turbine ratings, the battery storage sizes and the solar capacity often result in equally competitive Pareto optimal tradeoffs, therefore multi-modal behaviour is demonstrated by such systems. Recent studies that optimized hybrid renewable systems and power system dispatch in unpredictable and non-convex landscapes using multi-modal multi-objective evolutionary algorithms have empirically proven this phenomenon.

In reality, operators need a variety of high-quality configurations rather than just one ideal design, which they can select from according to their budget, risk tolerance, or environmental concerns. For example, studies have shown that renewable hybrid systems have several best settings, highlighting the need for algorithms that can find different Pareto-optimal regions. In a similar vein, multi-modal multi-objective techniques uncover hidden solution regions that are frequently overlooked by conventional algorithms, which is crucial for creating robust energy systems. Furthermore, it is clear that economic dispatch in contemporary power systems is intrinsically multi-modal, and algorithms that can find several globally competitive solutions under hierarchical distributed restrictions are needed to solve it. In light of this connection, the comparative analysis provided in this study is directly compatible and useful. The Large-Scale renewable designs, having numerous interacting components, are termed better suited for LERD's reformulated decision-variable approach. The MCCMO is often useful when having stringent operational restrictions like emission caps or grid stability, because of its robust treatment of constraint-dominated solution spaces. Moreover, the CMOEMT's multitasking method is particularly helpful when cost minimization and emission reduction need to be maximized synchronously as related activities. As a result, the suggested evaluation framework acts as a decision-support reference for choosing the best evolutionary strategy in actual renewable energy planning scenarios, in addition to benchmarking algorithmic performance.

III. LITERATURE REVIEW

This section of the paper discusses each algorithm mentioned in the introduction section in detail. The description is as follows:

A. Constrained Multi-Objective Optimization Based on Evolutionary Multitasking Optimization (CMOEMT)

It is an enhanced algorithm that solves multiple objective function problems and constraints. This algorithm applies evolutionary multitasking as an optimization function, which enables the tasks to be optimized simultaneously while taking advantage of the interaction between them. This algorithm incorporates approaches to address constraints and produce solutions to the objectives that fulfil the imposed restrictions [14]. This algorithm is described as a core mechanism implemented using a unified representation and a shared search space. This transfer is possible when applying an elaborate crossover and mutation scheme that would help to increase the diversity and, at the same time, reach the convergence. In addition, this algorithm uses a dynamic resource distribution approach to arrange the computational load to optimize resource utilization among the tasks [15]. The control of the evolution is also supported by the penalty functions, which adapt their penalty factor according to the current state of the population. As per the literature, this algorithm performs better than traditional multi-objective optimization methods, especially in cases with many interrelated constraints. This algorithm is termed preferable for dealing with real-life problems as it has the quality of search space exploration and holding a diversified pool of workable solutions [16].

B. Large-Scale MOEA based on DVA (LERD)

Another approach to solving the problems via the reformulation of decision variables is called LERD. It is the acronym of Large-Scale Evolutionary Algorithm based on Reformulated Decision Variables. By categorizing the decision variables according to how they affect diversity and convergence, this approach handles the problem of the curse of dimensionality

[17]. The algorithm uses the divide and conquer strategy, breaking down the complex issue into smaller, more manageable sub-problems. The reformulated DVA assists in locating and classifying the variables that play a major part in the optimization process, which results in the improvement of the efficiency of the algorithm. This algorithm has been applied successfully in several domains, which include complex system optimization, large-scale engineering design, and big data analytics, which demonstrates the capability of the algorithm to handle the high-demand decision spaces effectively [18].

C. Multi-Population Coevolutionary Constrained Multi-Objective Optimization (MCCMO)

An enhanced evolutionary technique known as Multi-Population Coevolutionary Constrained Multi-Objective Optimization (MCCMO) uses various coevolving populations to solve the CMOPs. Within this algorithm, each population is in charge of optimizing a subset of the restrictions or objectives. Through a coevolutionary mechanism, these populations communicate with one another and enhance overall performance [19]. This methodology broadens the range of potential solutions and facilitates the preservation of equilibrium between exploitation and exploration. The MCCMO has demonstrated efficacy in resolving the intricate optimization issues involving numerous competing goals and limitations, including supply chain optimization, environmental management, and logistics [20].

IV. RESEARCH GAP

Although there are advancements and improvements in the above-mentioned algorithms, there is still a gap that needs to be filled for the improvement of the capability and performance of these algorithms. There is still a need for work that focuses on addressing the actual scalability of these algorithms [21]. The LERD algorithm is comparatively better than others in solving the issues of the curse of dimensionality; however, a need still exists for more efficient strategies that can handle numerous DVAs without any degradation in performance [22]. In this overall scenario, the integration of modern artificial intelligence techniques such as reinforcement learning and deep learning is also an important gap that needs to be filled. For example, the deep reinforcement learning for adaptive operator selection in MCCMO and CMOEMT algorithms may enhance their capacity for the management of dynamic and complicated optimization environments. In addition to this, there is a requirement for stronger constrained handling methods in a bid to handle the highly non-convex and non-linear constraints that are prevalent in real-world applications [23]. For future optimization frameworks, a source of optimism is the hybrid algorithms. These algorithms have the potential of combining the strengths of the above-mentioned algorithms, which are LERD [24], CMOEMT [25], and MCCO [26]. Like, the coevolutionary mechanism of MCCMO and the variable analysis techniques of the LERD algorithm, combined with the multitasking ability of CMOEMT, may result in more adaptable and efficient optimization strategies. In conclusion, it is critical and vital to understand that the identified research gaps must be filled as soon as possible. Further comparative analysis and benchmarks are needed for the improvement of the algorithms provided and the assessment of the hefty number of tasks. The development of these algorithms in terms of the future will largely rely on a deeper comprehension of their strengths and weaknesses. If the identified research gaps are addressed closely, then it will help us in learning more about the limited multi-objective optimization and make these algorithms more useful in a variety of contexts [27].

V. BENCHMARK PROBLEM

A. *MMMOP1*

This problem type is designed to test the ability of an algorithm to find multiple Pareto-optimal solutions in a simple landscape. The objective functions are typically defined as follows:

$$f_1(x) = x_1,$$
$$f_2(x) = g(x) \times h\big(f_1(x), g(x)\big),$$
$$g(x) = 1 + 9\left(\sum_{i=2}^{n} \frac{x_i}{n-1}\right),$$
$$h(f_1, g) = 1 - \sqrt{\frac{f_1}{g}}; \qquad \text{Where, } x \in [0,1]^n$$

B. MMMOP2

This problem introduces more complexity by adding multimodality in the decision space. The equations are given by:

$$f_1(x) = x_1,$$
$$f_2(x) = g(x) \times h\big(f_1(x), g(x)\big),$$
$$g(x) = 1 + 9\left(\sum_{i=2}^{n} \frac{x_i}{n-1}\right),$$
$$h(f_1, g) = 1 - \left(\frac{f_1}{g}\right)^2; \qquad \text{Where, } x \in [0,1]^n$$

C. *MMMOP3*

This problem type focuses on creating a more rugged landscape with multiple local optima. The objective functions are:

$$f_1(x) = x_1,$$
$$f_2(x) = g(x) \times h\big(f_1(x), g(x)\big),$$
$$g(x) = 1 + 10\left(\sum_{i=2}^{n} \frac{x_i}{n-1}\right),$$
$$h(f_1, g) = 1 - \sqrt{\frac{f_1}{g}} - \left(\frac{f_1}{g}\right) \sin(10_{\pi} f_1); \qquad \text{Where, } x \in [0,1]^n$$

D. *MMMOP4*

This problem adds more complexity by introducing a sinusoidal component to the objective functions:

$$f_1(x) = x_1,$$
$$f_2(x) = g(x) \times h(f_1(x), g(x)),$$
$$g(x) = 1 + 10\left(\sum_{i=2}^{n} \frac{x_i}{n-1}\right),$$
$$h(f_1, g) = 1 - \sqrt{\frac{f_1}{g}} - \left(\frac{f_1}{g}\right)\sin(5_\pi f_1); \qquad \text{Where, } x \in [0,1]^n$$

E. *MMMOP5*

This problem type is designed to test the algorithm's ability to handle deceptive landscapes:

$$f_1(x) = x_1,$$
$$f_2(x) = g(x) \times h(f_1(x), g(x)),$$
$$g(x) = 1 + 9\left(\sum_{i=2}^{n} \frac{x_i}{n-1}\right),$$
$$h(f_1, g) = 1 - \sqrt{\frac{f_1}{g}} - \left(\frac{f_1}{g}\right)\sin(2_\pi f_1); \qquad \text{Where, } x \in [0,1]^n$$

F. *MMMOP6*

This problem introduces a more complex multimodal landscape with multiple peaks:

$$f_1(x) = x_1,$$
$$f_2(x) = g(x) \times h(f_1(x), g(x)),$$
$$g(x) = 1 + 9\left(\sum_{i=2}^{n} \frac{x_i}{n-1}\right),$$
$$h(f_1, g) = 1 - \sqrt{\frac{f_1}{g}} - \left(\frac{f_1}{g}\right)\sin(4_\pi f_1); \qquad \text{Where } x \in [0,1]^n$$

VI. SIMULATION RESULTS AND ANALYSIS

In this section, the simulation results of the comparison of the following EAs on the benchmark MMO functions are presented. Table 2 illustrates the algorithm performance based on the benchmark performance measures. Table 1 shows the parameters that are used in measuring the performance of the algorithms.

The following is the detail of the results of each algorithm with respect to multi-modal multi-objective problems:

A. MMMOP1

- **CMOEMT**: Shows moderate runtime (4.99E+00) with good CPF (8.46E-01) and DM (9.00E-01). It has a low GD (2.60E-04) and decent HV (5.80E-01).
- **LERD**: Slightly higher runtime (5.79E+00) but better CPF (9.25E-01) and DM (9.33E-01). It also has a low GD (7.53E-05) and comparable HV (5.82E-01).
- **MCCMO**: Significantly higher runtime (1.12E+00) with good CPF (8.73E-01) and DM (9.24E-01). It has a low GD (1.08E-04) and comparable HV (5.81E-01).

B. MMMOP2

- **CMOEMT**: Moderate runtime (7.33E+00) with good CPF (8.39E-01) and DM (8.16E-01). Low GD (9.36E-05) and decent HV (3.47E-01).
- **LERD**: Lower runtime (1.73E+00) but lower CPF (6.77E-01) and DM (6.64E-01). Very low GD (3.49E-05) but lower HV (3.04E-01).
- **MCCMO**: Moderate runtime (6.14E+00) with good CPF (8.08E-01) and DM (7.82E-01). Low GD (5.65E-05) and comparable HV (3.30E-01).

Table 1: Performance Parameters and their Description

Performance Parameter	Description
Runtime	The time taken to complete the optimization process.
CPF (Convergence Performance Factor)	Measures how well the algorithm converges to the Pareto front.
DM (Diversity Metric):	Assesses the diversity of solutions.
DeltaP	Measures the spread of the solutions along the Pareto front.
GD (Generational Distance):	The average distance of the solutions from the true Pareto front.
HV (Hypervolume):	The volume covered by the Pareto front solutions.
IGD (Inverted Generational Distance)	Measures both convergence and diversity.
IGDX	A variant of IGD focusing on extreme points.
IGDp	A variant of IGD focusing on the Pareto front.
PD (Pareto Diversity)	Measures the spread and distribution of solutions.
Spacing	Measures the uniformity of the distribution of solutions.
Spread	Measures the extent of the spread of solutions.

C. MMMOP3

- **CMOEMT**: Higher runtime (8.30E+00) with good CPF (8.35E-01) and DM (8.13E-01). Low GD (3.40E-04) and decent HV (3.47E-01).

- **LERD**: Moderate runtime (3.82E+00) with good CPF (7.72E-01) and DM (7.99E-01). Higher GD (1.39E-03) but comparable HV (3.46E-01).
- **MCCMO**: Moderate runtime (6.65E+00) with good CPF (8.62E-01) and DM (8.23E-01). Low GD (4.59E-04) and comparable HV (3.47E-01).

D. MMMOP4

- **CMOEMT**: Moderate runtime (5.53E+00) with good CPF (8.46E-01) and DM (8.19E-01). Low GD (5.46E-04) and decent HV (3.47E-01).
- **LERD**: Higher runtime (5.32E+00) with good CPF (7.86E-01) and DM (7.97E-01). Higher GD (3.34E-03) but comparable HV (3.46E-01).
- **MCCMO**: Lower runtime (3.47E+00) with good CPF (8.66E-01) and DM (8.21E-01). Low GD (8.51E-05) and comparable HV (3.47E-01).

E. MMMOP5

- **CMOEMT**: Moderate runtime (5.59E+00) with good CPF (8.46E-01) and DM (8.26E-01). Low GD (1.35E-04) and decent HV (3.47E-01).
- **LERD**: Higher runtime (6.09E+00) with good CPF (7.83E-01) and DM (7.87E-01). Low GD (5.02E-05) but comparable HV (3.47E-01).
- **MCCMO**: Lower runtime (3.48E+00) with good CPF (8.66E-01) and DM (8.27E-01). Low GD (5.87E-05) and comparable HV (3.47E-01).

F. MMMOP6

- **CMOEMT**: Moderate runtime (5.34E+00) with lower CPF (7.10E-01) and DM (7.57E-01). Higher GD (4.35E-04) and decent HV (3.41E-01).
- **LERD**: Moderate runtime (4.48E+00) with lower CPF (7.18E-01) and DM (7.24E-01). Higher GD (1.86E-04) but comparable HV (3.28E-01).
- **MCCMO**: Lower runtime (3.11E+00) with lower CPF (7.13E-01) and DM (7.52E-01). Higher GD (3.18E-04) and comparable HV (3.38E-01).

Findings

- **CMOEMT** generally shows good performance in terms of CPF and DM across most MMMOPs, with moderate runtime.
- **LERD** often has lower runtime but shows variability in CPF and DM, with some instances of higher GD.
- **MCCMO** tends to have higher runtime but maintains good CPF and DM, with low GD and comparable HV.

Table 2: Performance Comparison

MMMOP#	Algorithm	Runtime	CPF	DM	DeltaP	GD	HV	IGD	IGDX	IGDp	PD	Spacing	Spread
MMMOP1	CMOEMT	4.99E+00	8.46E-01	9.00E-01	4.59E-03	2.60E-04	5.80E-01	4.59E-03	1.62E-01	3.96E-03	1.72 E+03	3.62E-03	1.58E-01
MMMOP2	CMOEMT	7.33E+00	8.39E-01	8.16E-01	4.29E-03	9.36E-05	3.47E-01	4.29E-03	1.83E-01	2.19E-03	1.66 E+03	3.93E-03	1.61E-01
MMMOP3	CMOEMT	8.30E+00	8.35E-01	8.13E-01	4.28E-03	3.40E-04	3.47E-01	4.28E-03	9.36E-02	2.17E-03	1.69 E+03	6.09E-03	1.83E-01
MMMOP4	CMOEMT	5.53E+00	8.46E-01	8.19E-01	4.69E-03	5.46E-04	3.47E-01	4.47E-03	1.36E-01	2.36E-03	1.75 E+03	7.43E-03	1.87E-01
MMMOP5	CMOEMT	5.59E+00	8.46E-01	8.26E-01	4.55E-03	1.35E-04	3.47E-01	4.55E-03	1.49E-01	2.35E-03	1.71 E+03	3.98E-03	1.67E-01
MMMOP6	CMOEMT	5.34E+00	7.10E-01	7.57E-01	9.35E-03	4.35E-04	3.41E-01	9.28E-03	3.92E-01	5.29E-03	1.40 E+03	8.09E-03	3.07E-01
MMMOP1	LERD	5.79E+00	9.25E-01	9.33E-01	3.77E-03	7.53E-05	5.82E-01	3.77E-03	2.79E-01	2.94E-03	1.82 E+03	1.76E-03	7.07E-02
MMMOP2	LERD	1.73E+00	6.77E-01	6.64E-01	1.27E-02	3.49E-05	3.04E-01	1.27E-01	4.61E-01	6.45E-02	1.13 E+03	5.48E-03	3.62E-01
MMMOP3	LERD	3.82E+00	7.72E-01	7.99E-01	4.96E-03	1.39E-03	3.46E-01	4.45E-03	1.54E-01	2.36E-03	1.53 E+03	1.84E-02	3.53E-01
MMMOP4	LERD	5.32E+00	7.86E-01	7.97E-01	6.77E-03	3.34E-03	3.46E-01	4.47E-03	2.55E-01	2.31E-03	1.54 E+03	3.79E-02	3.48E-01
MMMOP5	LERD	6.09E+00	7.83E-01	7.87E-01	4.24E-03	5.02E-05	3.47E-01	4.24E-03	2.43E-01	2.20E-03	1.59 E+03	6.99E-03	2.70E-01
MMMOP6	LERD	4.48E+00	7.18E-01	7.24E-01	4.90E-03	1.86E-04	3.28E-01	4.90E-02	5.12E-01	2.76E-02	1.48 E+03	7.09E-03	3.50E-01
MMMOP1	MCCMO	1.12E+00	8.73E-01	9.24E-01	4.00E-03	1.08E-04	5.81E-01	4.00E-03	2.71E-01	3.27E-03	1.73 E+03	3.16E-03	1.41E-01
MMMOP2	MCCMO	6.14E+00	8.08E-01	7.82E-01	5.34E-03	5.65E-05	3.30E-01	5.34E-02	3.55E-01	2.69E-02	1.53 E+03	3.28E-03	1.93E-01
MMMOP3	MCCMO	6.65E+00	8.62E-01	8.23E-01	4.39E-03	4.59E-04	3.47E-01	4.19E-03	1.24E-01	1.91E-03	1.69 E+03	6.97E-03	1.68E-01
MMMOP4	MCCMO	3.47E+00	8.66E-01	8.21E-01	4.29E-03	8.51E-05	3.47E-01	4.29E-03	2.32E-01	2.23E-03	1.65 E+03	3.50E-03	1.40E-01
MMMOP5	MCCMO	3.48E+00	8.66E-01	8.27E-01	4.29E-03	5.87E-05	3.47E-01	4.29E-03	2.09E-01	2.12E-03	1.71 E+03	3.51E-03	1.43E-01
MMMOP6	MCCMO	3.11E+00	7.13E-01	7.52E-01	1.64E-02	3.18E-04	3.38E-01	1.64E-02	4.23E-01	8.19E-03	1.47 E+03	1.22E-02	3.58E-01

The following are the figures 1 till 12, which are visual representations of the presented table; each figure presents a comparison with respect to the performance metric to the CMOEMT, LERD, and MCCMO.

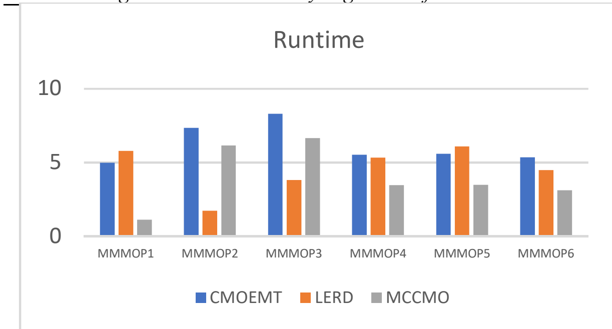

Figure 1: Runtime comparison of CMOEMT, LERD, and MCCMO

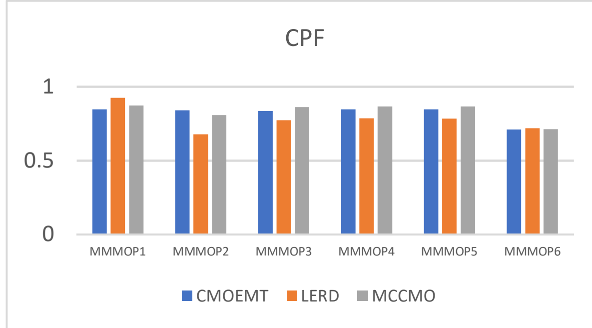

Figure 2: CPF comparison of CMOEMT, LERD, and MCCMO

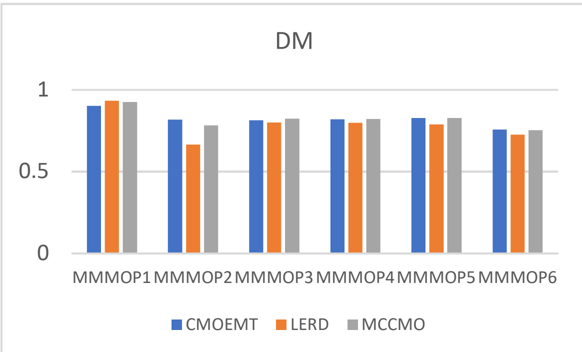

Figure 3: DM comparison of CMOEMT, LERD, and MCCMO

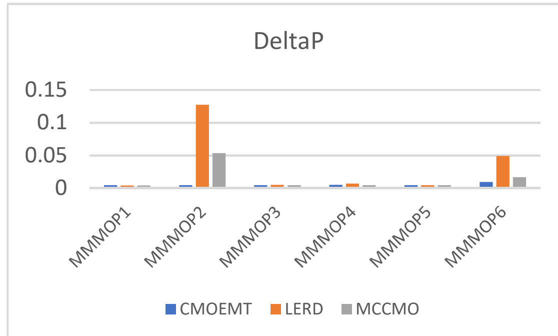

Figure 4: DeltaP comparison of CMOEMT, LERD, and MCCMO

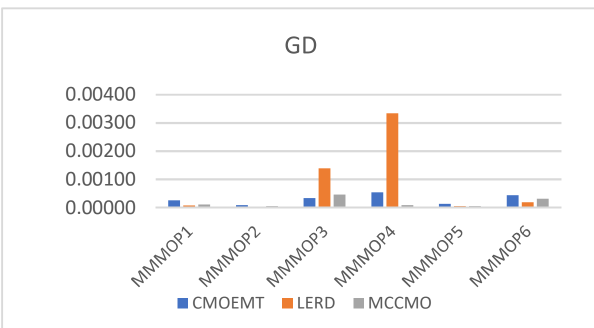

Figure 5: GD comparison of CMOEMT, LERD, and MCCMO

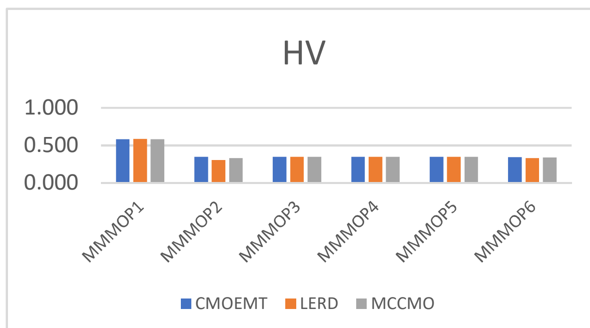

Figure 6: HV comparison of CMOEMT, LERD, and MCCMO

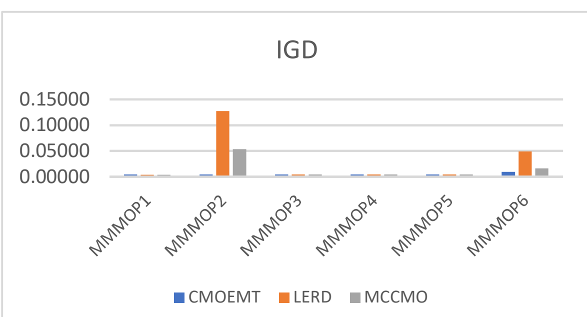

Figure 7: IGD comparison of CMOEMT, LERD, and MCCMO

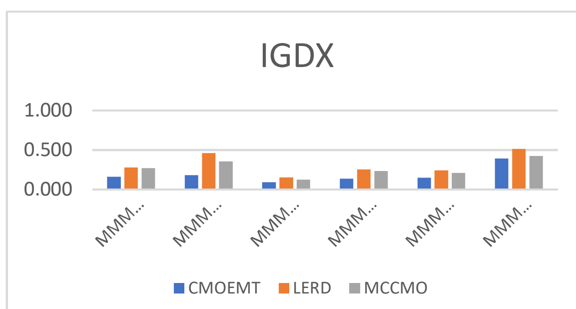

Figure 8: IGDX comparison of CMOEMT, LERD, and MCCMO

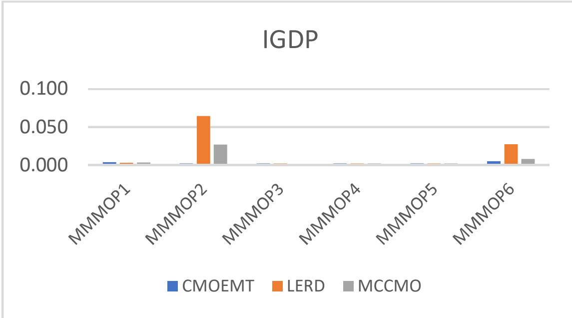

Figure 9: IGDP comparison of CMOEMT, LERD, and MCCMO

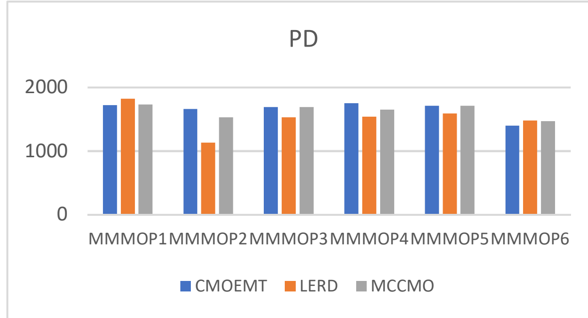

Figure 10: PD comparison of CMOEMT, LERD, and MCCMO

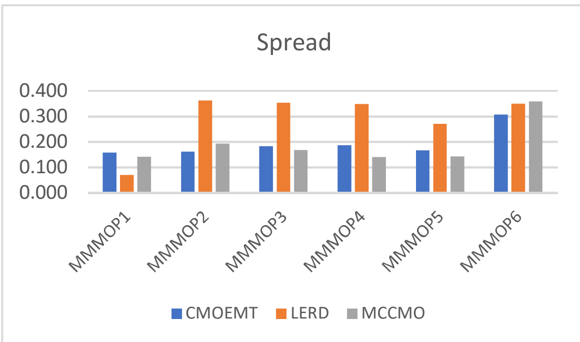

Figure 11: Spread Comparison of CMOEMT, LERD, and MCCMO

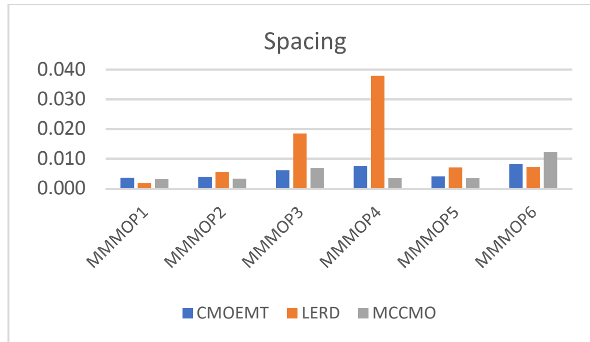

Figure 12: Spacing Comparison of CMOEMT, LERD, and MCCMO

VII. CONCLUSION

This research has presented a comprehensive comparison of the three modern evolutionary algorithms (CMOEMT, LERD, and MCCMO) over the six-benchmark multimodal multi-objective problems. According to the findings of the study, each of the algorithms gave distinct performance advantages as per the characteristics of the problem. This means that rather than searching for a one-size-fits-all solution, this work provides the choice that is vital for solving the problem. CMOEMT performed well where there was a requirement for balanced convergence and diversity. LERD has shown vital and greater performance on the large-scale problems, especially where the decision variables meaningfully influence the convergence. Whereas MCCMO proved to be best in the environments conditioned with strict constraints and multimodal landscapes, thus offering strong convergence and diversity at the cost of runtime. The performance matrix presented in this work provides a vital opportunity for practitioners to select the most appropriate algorithm objectively for real-world applications. Future work should aim to tackle scalability, integrate advanced techniques, handle constraints robustly, develop hybrid algorithms, and conduct extensive benchmarking to further advance these optimization strategies.

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