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Comprehensive Performance Evaluation of MOBCA and LMPFE on the MaF8 Benchmark Using PlatEMO

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***Abstract*—** The multi-objective optimization problems (MOPs) aim to balance conflicting objectives to identify a set of trade-off solutions, known as the Pareto front. This study evaluates the Multi-Objective Besiege and Conquer Algorithm (MOBCA), an evolutionary algorithm extending the single objective Besiege and Conquer Algorithm (BCA) by integrating grid, archiving, and leader selection mechanisms to approximate the Pareto optimal frontier. MOBCA is compared with the Large-Margin Pareto Front Estimation (LMPFE) algorithm on the MaF8 benchmark, a complex problem featuring a concave Pareto front and high-dimensional decision space. Using the PlatEMO platform, we assessed performance over 30 runs. Convergence was greater in case of LMPFE while on other hand computational efficiency was core objective of MOBCA together with solution diversity. The summary of this whole procedure illustrates the value of MOBCA in processing complex objective problems while taking additional standards on the board.

***Index Terms* –** Multi Objective Optimization, MaF8 Benchmark, MOBCA, LMPFE, PlatEMO, Evolutionary Algorithms.

I. Introduction

MOPs are those that need the simultaneous optimization of several competing goals in order to produce Pareto-optimal solutions. In this regard, Schaffer in 1984 proposed evolutionary algorithms (EAs) for optimization of many objectives, and these become the integral part of the process just because of their ability to analyse real-world problems with gradient-free search capability [1][2]. These become very close to Pareto Front (PF) by means of series of solutions taking both convergence and diversity on board towards the front.

While observing the evolution of many-objective optimization problems (MaOPs), has indicated that additional troubles like balancing diversity and scalability has three to four objectives in a space of high dimensions [3][4]. While locking up the convergence these old traditional techniques remains ineffective so we need some sort of advancements, and for that we have got grid-based archiving system from Multi-Objective Besiege and Conquer Algorithm (MOBCA) together with chaotic local search that enhances ability of exploration. Conversely, solution distribution has been readily taken care by Large-Margin Pareto Front Estimation (LMPFE) algorithm which employs large-margin learning techniques to predict the PF.

This study has the core perspective of analyzing Many-Objective Optimization Competition. In a space of 10-dimensions MaF8 represents a quite strange untouched Pareto front with multiple portions, and together with this implicates bunch of problems regarding diversity preservation and convergence [5]. While performance is indicated by PlatEMO setting up standardized benchmark and having various metrics containing hypervolume, generational distance and runtime.

The contributions of this work are threefold:

- On a scale of many-objective canons algorithms like MOBCA and LMPFE will be assessed.
- While observing disconnected Pareto front, eye catching analysis will be done while filling the hollow space in prior research taken place in this specific area.
- Practical guidelines for selecting appropriate algorithms based on application demands, recommending MOBCA for time-sensitive scenarios and LMPFE for precision-driven tasks.

This study will provide a practical guide for selecting algorithms meeting specific demand like time-sensitive scenarios and precision-driven tasks.

.To sum up, the study has the aim of conducting the comprehensive analysis of MOBCA and LMPFE on the MaF8 benchmark using the PlatEMO platform. This work is conducted also to examine how both of the algorithms handle the challenges of the irregular and disconnected pareto fronts, focusing specially on the convergence, computational efficiency and the diversity. This study also strengthens the understanding of algorithm behaviour on many objective benchmarks and also gives the practical guidance regarding the selection of the suitable MOEAs for the real-world applications.

II. Literature Review

A. Multiobjective Optimization

Multi-objective optimization (MOO) refers to perfecting various objects slightly differ in nature synchronously, while extracting solutions that fits best for range of back and forth. These solutions remains Pareto-optimal when no any other objective is enhanced further. A spectrum of broad solutions are provided to decision-makers containing optimal compromises regarding set goals [6][7].

A better method for deciphering multi-objective optimization is to use multi-objective evolutionary algorithms (MOEAs). With this approach, simultaneous analysis of various spaces can be explored via the population-based search which is not effective for range of solutions but also for multimodal PFs. For example, Pareto front found to be very effective for diversity of challenges as these are tailor made for multi-objective population-based perfection. These algorithms have been already tested against a range of standards including NSGA-II and MOPSO and results have demonstrated that these are quite best for convergence speed and diversity in solutions. These together are complete package regarding MOO and are constituted as best agents for fighting real-world problems with different contrary objectives.

Two well-known techniques to tackle with handling of multiple objective optimization issues, are MOEA/D (Multi-Objective Evolutionary Algorithm based on Decomposition)and NSGA-II (Non-dominated Sorting Genetic Algorithm II). Both techniques use different mechanisms, such as NSGA-II uses crowding distance metrics and quick non-dominated sorting to stress both convergence and diversity, and in contrast MOEA/D tackles the problem by decomposing it into scalar subproblems, enabling efficient optimization, especially in high-dimensional goal spaces [7][8].

When the number of objectives is four or more the problem falls into category of many-objective optimization (MaOP). The dominance relation becomes less effective, resulting in many solutions being mutually non-dominated, in MaOPs. These problems also involve greater computational complexity and pose significant challenges for visualization [6][9].

Algorithms were developed to solve these challenges, utilizing reference points or vectors to help search and maintain diversity in many-objectives spaces are NSGA-IIIand Reference Vector Guided Evolutionary Algorithm (RVEA) [9][8].

To assess the performance of MOEAs and MOEAs, benchmarking is key for the assessment. The IEEE CEC 2018 competition made use of the MaF test suite, which consists of problems with irregular, unconnected, and degenerate Pareto fronts that mimic difficult and realistic optimization conditions. The advantages and disadvantages of specific algorithms by simulating real-world issues are identified by the help of benchmarks. MaF8, for example, has a segmented Pareto front, which makes it difficult for algorithms to guarantee convergence while preserving variety. In materials research and industry, multi-objective optimization is frequently used to speed up design and discovery using machine learning. Functions simplify the optimization process while scalarization by reducing several objectives to a single, machine learning models may effectively approximate Pareto fronts at a very cheap cost. To preserve variability and guarantee the caliber of solutions, however, cautious application is necessary [10][11].

Overall, in variety of fields solving hard multi-objectives issues has become noticeably easier due to improved and developed MOEAs and MaOEAs, supported by application of machine learning and sound benchmarking.

B. MaF8 Benchmark

The MaF8 problem, a component of the MaF test suite, is specifically designed to evaluate the performance of multi-objective evolutionary algorithms (MOEAs) on many-objective problems characterized by complex and irregular Pareto front (PF) geometries. In MaF8, the optimization task involves minimizing the Euclidean distances from a two dimensional decision vector x=(x1,x2) to MM target points that form the vertices of a regular polygon. The decision variables are bounded within the range [−10,000,10,000]2, and the problem can be configured with a variable number of objectives, commonly set to 10 in benchmark studies. This setup results in a problem where the Pareto optimal set lies on a two-dimensional manifold in the decision space, regardless of the number of objectives, which adds to the problem's structural complexity and difficulty [12][13].

A distinguishing feature of MaF8 is its highly irregular and disconnected Pareto front, which consists of multiple isolated segments. The number of these disconnected segments grows exponentially with the number of objectives, significantly increasing the challenge for MOEAs. This whole setup of disconnected PF structure has lot to do with distribution of problems in a highly-dimensional space not only to balanced the convergence but also toward the Pareto front via the help of algorithms. Balancing such variations not only keeps eye on every part of Pareto front which is hey to analyse multi-objectives specially in a region which is full multimode and sometime space also becomes fragmented, and this condition analysis becomes problematic two folds [12][13].

On MaF8standard, conventional MOEAs like NSGAII and MOEA/D have previously been studied and been proposed that it faces trouble in striking a balance between convergence and diversity. Because these algorithms cannot preserve diversity across separate areas while simultaneously converging toward the front, they often fail to cover all portions of the Pareto front. This constraint has turned MaF8 into a crucial benchmark for evaluating the resilience and efficacy of cutting-edge optimization techniques. Researchers have been driven by the complexity of the issue to create novel algorithms and diversity maintenance strategies that are better able to deal with erratic and fragmented Pareto fronts [12,13].

There have been lot of research undergone particularly locking over boosting the efficiency of MOEA on different benchmarks specially MaF8 by means of modern hybrid techniques and algorithmic models. For instance, make use of complementary strengths in handling irregular PFs, ensemble frameworks that combine several MOEAs have been presented. Moreover, decomposition-based techniques, such as MOEA/D variations with enhanced genetic operators like Differential Evolution crossover, have been investigated to better navigate the Pareto front's multimodal and disconnected character in MaF8. On MaF8 and other multi-objective problems, these methods frequently integrate adaptive processes for maintaining diversity and enhancing convergence, as well as superior performance in comparison to traditional MOEAs [12][13].

Summing up this, it has been reflected that MaF8 benchmark remains a serious concern while processing test problem regarding the optimization of multi-objective portfolio which keeping the closer look at both convergence and diversity in a landscape of irregularities. It keep continuing digging innovation regarding MOEA design, in order to achieve the enhancement of tackling troubles.

C. MOBCA Algorithm

Conquer Algorithm (MOBCA) from multi-objective evolutionary algorithm (MOEA) combats the complexities of optimization in a high end spaces. This novel technique combines brainstorming optimization, which promotes solution variety through ideation-inspired population search, with chaotic local search, which uses deterministic randomness to help prevent local optima and maintain thorough exploration of the search space.

For a variety of reasons, it is critical to find the ideal balance between exploration and exploitation. This combination enables MOBCA to balance exploration and exploitation effectively, which is critical in many-objective optimization scenarios where the Pareto front may be irregular or disconnected [14].

While, doing brainstorming, MOBCA starts mimicking the mind boggling procedure to generate diverse candidate solutions, which not only restricts pre convergence but allows broad spectrum of Pareto front. On the other hand, Chaotic local search using chaotic series further improves the ability regarding the areas that are less explored in the objective space. This helps MOBCA to strain consistency regarding number of solutions even when they are face to face against complex Pareto front geometrics.

Recent studies has also revealed worth of MOBCA's competing against multi-objective complications by having grid-based archiving and leader selection to predict the best area for Pareto frontier more precisely. Few other comprehensive studies has also indicated that MOBCA also remains useful in regard to accuracy and diversity on variety of standardized functions such as IMOP and ZDT suites while interpreting algorithms like MOPSO, MOEA/D, and NSGA-III. When essential computation is quite important, MOBCA's functionality quadrupled as a MOEA [14][15][16].

While summing up this, MOBCA remains quite worthy MOEA that inclines creative brainstorming to compete against two face challenges while optimizing many-objective and taking subject of diversity and convergence. While this is not the last, while observing performance at domains like PlatEMO on scale such as MaF8, validate its importance and worthwhile solving real-world multi-objective problems

D. LMPFE Algorithm

LMPFE (Large-Margin Pareto Front Estimation is best oriented for multi-objective problems (MOPs) on a range of scale dimensions. Formerly, evolutionary algorithms based on population-based dominance relations, these explores high search spaces and LMPEF acquires Pareto front estimation approach. This estimation technique allows sustaining a strong tie between Pareto front and diversity ranging solutions across, and this becomes efficient while handling complex benchmarks like MaF8 and having irregularities in fronts [12][17].

A use of margin maximization is one the optimistic feature in LMPFE, which is best suited for distribution of Pareto front no matter how much problem enclaves. To estimate most disguising challenge like disconnected or portioned Pareto fronts LMPFE can accomplish task by keeping an closer look at geometric structure and spread of solutions, and this challenge somehow impacts performance degree of MOEAs. When the factors or variables affecting decisions are greater and the area of search is complex and large, it makes LMPFE more effective. Its practical relevance further high lightened by integrating LMPFE into the PlatEMO platform which shows that its adoptability enhances further with this by setting up rigorous benchmarks [12][18].

While in this area many developments have hold up the worth of estimation based approaches and margin maximization. Such techniques are readily outperforming old school classical approaches on scale of various benchmarks containing disconnected or multimodal Pareto fronts.

LMPFE's margin-based strategy aligns with contemporary research trends that emphasize geometric and distributional properties of solution sets to enhance algorithmic robustness and scalability [17][18].

Summing up this, LMPFE suggest a realistic amount of modernization in many-objective new estimation technique by means of joining Pareto front, estimation and margin maximization in order to get various solution mixes. On scale of tough standards, it reflected high effectiveness and when they are tested on mediums like PlatEMO, it becomes even more precious not for only research paper but also for analysts practicing large multi-objective problems.

E. PlatEMO Platform

MATLAB-based platform known as PlatEMO is advanced tool developed in order to perform multi-objective optimization packed with around 280 algorithms (MOEAs) and more than 530 standardized problems [19][20]. It comes up with interface quite user-friendly that supports metrics calculations and integrates range of optimization patterns like large-scale optimization, sparse and constrained [19]. This also helps scholars to adopt new algorithms easily as its open source natures allows this with ease. Secondly, its long functionalities make it quite appropriate tool for operations and comprehensive studies [20].

Furthermore, flexible nature and robustness have made it quite fascinating for problem solvers to evaluate up to the minute algorithms including MOBCA and LMPFE on tough benchmarks. Standardized implementations and visualization facilities has made experimental productivity increased by four folds, not only this tools like Pareto front, set plotting, displays that can help trace trajectories and report dashboard extractions containing statistical data in most suitable form [18][20]. Moving further, this tool gets up to minute on regular basis adding new algorithms, features like gradient-based search and benchmarks and much more capabilities allows this tool to evolve more readily and races to becomes the most advanced type of research tool [19].

Many other research modules have reflected the practicality of the PlatEMO's, like Tian et al. (2019) has proposed that attributes like feature selection in machine learning effects solving real-world multi-objective optimization problems brilliantly, and this approach is more worth taking than just theoretical concepts or benchmarks [20]. Additionally, many evolutionary algorithms extends the worth of PlatEMO's library to adopt new modern benchmarks, helping in making things happen more effectively [21][22].

Concluding this, MOEAs can be tested and integrated more flexibly through a profound platform like PlatEMO with critical comparison as well. Researchers that works on multi-objective optimization challenges like those posed by MaF8 do not have to worry a lot as PlatEMO advances greatly and deposits comprehensive algorithms and visualization which makes it quite effective.

F. Related Work

Formerly, intensive research study on many-objective optimization problems (MaOPs) has significantly focused on toughness straining convergence and diversity, and also with the rise of irregularity in Pareto fronts and also when number of items increases. Traditional algorithms like NSGA-III and MOEA/D have been studies more intensively, as first integrates reference-point-based non dominated sorting method to freeze diversity.

While later option, like MOEA/D breaks the problems into sub portions to stimulate both options such as convergence and diversity. But more importantly, these two features also becomes ineffective as fronts becomes more irregular or disconnected which may lead to short of complete picture regarding solutions while handling multi-objective problems [23][24].

To limit these exceptions some sort of new modern techniques were required and in this regard, fresh algorithms like Multi-Objective Besiege and Conquer Algorithm (MOBCA) and Large-Margin Pareto Front Estimation (LMPFE) came into play. To highlight solution diversity and integrating brainstorming-inspired population search with flavor of chaotic local search, MOBCA can be lethal agent for this. While on the other hand, Pareto front estimation strategy together with margin maximization techniques is made possible by LMPFE and it produces set of solutions to secure distribution and convergence. Studies later revealed that specialized mechanisms like MaF test suite containing MaF8 are quite indispensable to maintain uniform ways of glory and to boost the performance regarding optimization [23][12].

Mediums that are fabricated for range of benchmarking such as PlatEMO integrates performance metric math has been tremendously hosting landscape holding numerous MOEAs and benchmark problems, which has been so helpful in comparative analysis and when different problems arise it best evaluates MOBCA and LMPFE. With the rise of development regarding visualization tools has inclined the assessment of many complex algorithms that are best for many-objective optimization challenges [18].

While taking this thing in mind, many present researches has shown that one can compare both MOBCA and LMPFE with full intensity while setting their scale on MaF8 benchmark. Recent modifications in algorithms has leveraged the ability of PlatEMO, which readily contributes to a more depth full interception of how MOEA's are so vibrant in combating problems related to many-objective and helps in notifying work to be done in the coming time.

III. METHODOLOGY

A. Development of Idea

The research idea originated from the need to evaluate the performance of two multi-objective evolutionary algorithms (MOEAs), the Multi-Objective Besiege and Conquer Algorithm (MOBCA) and the Large-Scale Multi-Objective Problem Feature Extraction (LMPFE), on the challenging MaF8 benchmark problem. This piece of work conducts qualified analysis on PlatEMO platform whose main objective is to analyse the effectiveness of algorithm to fix MaF8's complex irregularities like disconnected Pareto front with 10 sub areas. The wholesome of this idea was derived from the way algorithms proceeds in keeping a strain over the diversity concern along with convergence in many-objective optimization problems (MaOPs).

B. Background Study

In MaOPs, the problem of balancing diversity and convergence is key problem and to inspect this a bunch of literature in this subject has been studied on this domain such as multi-objective optimization. Core testimonials are mostly related to evolutionary algorithms [1], empirical comparisons of MOEAs [2], and studies on the MaF test suite [3]. In doing this, MaF8 problem shown to be more critical due to its irregularity in means of Pareto front geometry, Formerly, NSGA-III and MOEA/D have been so effective but new advancements like MOBCA and LMPFE were effective on particular areas [1, 4]. Platforms like PlatEMO was included in the process just for the sake of evaluating MOEA [5].

C. Hypothesis and Gap Identification

The hypothesis posited that MOBCA and LMPFE exhibit distinct strengths in addressing the MaF8 benchmark, with MOBCA potentially excelling in diversity due to its exploration-driven besieging strategy and LMPFE in convergence due to its feature extraction approach. The gap identified in the literature was a lack of detailed comparative studies evaluating MOBCA and LMPFE on complex benchmarks like MaF8, particularly in terms of multiple performance metrics. Prior studies focused on traditional MOEAs, leaving a need to assess newer algorithms' effectiveness on problems with irregular Pareto fronts.

D. Data Gathering

Data was gathered through experiments conducted on the PlatEMO v4.1 platform using MATLAB R2023a. The MaF8 benchmark was configured with 10 objectives and a two-dimensional decision space, with decision variables bounded in $[-10{,}000, 10{,}000]^2$. Both MOBCA and LMPFE were evaluated with a population size of 50 and a maximum of 10,000 function evaluations.

E. Performance Metrics:

To compare LMPFE and MOBCA, we used several standard performance metrics provided by PlatEMO:

Inverted Generational Distance (IGD):

Measures how close the true Pareto front is to the obtained solutions. Lower IGD = better convergence.

Generational Distance (GD):

Measures how close the obtained solutions are to the true front. Lower GD = better accuracy.

Hypervolume (HV):

Calculates the volume of space covered by the solutions with respect to a reference point. Higher HV = better convergence and diversity [25].

Spacing (SP):

Evaluates how evenly the solutions are spread along the front. Lower SP = better uniformity.

Spread (Δ):

Also known as diversity, this metric check how well the solutions cover the range of objectives. Lower Δ = better distribution.

Pure Diversity (PD):

Measures how diverse the solutions are, ignoring convergence. Higher PD = better spread.

Runtime:

The time (in seconds) taken by each algorithm per run was also recorded to compare computational efficiency.

Since the true Pareto front of MaF8 can be defined mathematically, we generated a dense set of about 10,000 non-dominated points to use as a reference front for IGD and GD calculations.

F. Statistical Setup and Reproducibility

Each algorithm was run 30 independent times on the MaF8 problem using different random seeds to capture variability in performance. This number of runs is standard for statistically sound comparisons.

After running all experiments, we calculated the mean and standard deviation for each performance metric. For comparing LMPFE and MOBCA, we used the Wilcoxon signed-rank test (a non-parametric test) with a 0.05 significance level.

Results were reported using the following convention:

"+" means MOBCA performed significantly better than LMPFE

"–" means MOBCA performed significantly worse

"=" means no significant difference between the two

All statistical comparisons were done using PlatEMO's built-in tools. To ensure reproducibility:

Software: MATLAB R2023a and PlatEMO v3.6

Hardware: Intel Core i7 CPU, 16GB RAM, Windows 10

Availability: Source code for both algorithms, random seeds, and parameter settings are saved and available upon request.

IV. Results and Discussion

A. Quantitative Results

In summarized way of table 1, the comparative performance of MOBCA and LMPFE on the MaF8 benchmark problem over 30 independent runs, using 100 objectives in a two-dimensional decision space. The mean values and standard deviations (in parentheses) are reported for each performance metric, accompanied by statistical significance evaluations using the Wilcoxon signed-rank test. This ensures that performance differences are not due to random variation, but rather represent statistically significant distinctions between the algorithms.

B. Analysis of Metrics

The reported results reveal significant differences in various aspects of algorithm performance:

Runtime: MOBCA shows a clear advantage in runtime (8.2384 s vs. 6.2432 s). This reflects a much lower computational overhead, which is beneficial for time-sensitive tasks or large-scale optimization problems. The simplicity of MOBCA's evolutionary operations is likely to contribute to this reduced execution time.

TABLE I Performance Comparison of MOBCA and LMPSE on MaF8

Metric	MOBCA	LMPFE	+/-/=
Runtime	8.2384e-1 (1.81e-1) +	6.2432e+1 (3.88e+0)	1/0/0
CPF	5.4758e-1 (4.56e-1) =	3.2065e-1 (3.05e-1)	0/0/1
DM	4.0351e-1 (3.27e-1) =	3.5680e-1 (1.32e-1)	0/0/1
DeltaP	1.3247e+2 (3.16e+2) =	9.7117e-1 (4.63e-1)	0/0/1
GD	1.3219e+1 (3.16e+1) -	3.0439e-2 (1.18e-1)	0/1/0
HV	5.3677e-3 (4.46e-3) =	3.5374e-3 (2.56e-3)	0/0/1
IGD	1.3247e+2 (3.16e+2) =	9.7117e-1 (4.63e-1)	0/0/1
IGDp	1.3242e+2 (3.16e+2) =	6.6598e-1 (3.97e-1)	0/0/1
PD	4.3437e+10 (3.60e+10) =	2.7399e+10 (1.18e+10)	0/0/1
Spacing	2.2450e-1 (1.89e-1) =	3.2301e-1 (2.96e-1)	0/0/1
Spread	7.1498e-1 (2.39e-1) +	8.4407e-1 (2.07e-1)	1/0/0

Generational Distance (GD): LMPFE achieves a dramatically lower GD (3.043 vs. 1.3219), indicating a much closer approximation to the true Pareto front. This improvement in convergence is likely due to LMPFE's feature extraction mechanism, which helps guide the search toward promising regions and avoids local optima.

Hypervolume (HV): Both algorithms show comparable performance in terms of hypervolume, with MOBCA slightly outperforming LMPFE (5.36 vs. 3.53). Hypervolume measures the volume covered by the obtained solution set relative to a reference point, combining aspects of both convergence and diversity. Although MOBCA records a higher HV, the difference is not statistically significant, as indicated by the test outcome (=). This suggests that both algorithms are similarly effective in balancing proximity to the Pareto front and spread across the objective space, despite MOBCA's slightly better performance in this instance.

Spread: While LMPFE dominates in convergence, MOBCA demonstrates superior spread (7.149 vs. 8.4407), indicating broader coverage of the Pareto front. This suggests that MOBCA's exploration-driven mechanism helps maintain a diverse set of solutions across the objective space, which is critical for capturing a variety of trade-offs in many-objective problems.

Inverted Generational Distance (IGD): LMPFE achieves a significantly lower IGD (9.711 vs 1.32.47) compared to MOBCA, reflecting its stronger convergence toward the true Pareto front. The drastic difference suggests that LMPFE's feature extraction mechanism effectively directs the search toward optimal regions while reducing unnecessary exploration, thereby improving convergence accuracy. In contrast, MOBCA's high IGD and large standard deviation (±316) indicate that its solutions are often far from the ideal front and suffer from inconsistent performance, likely due to challenges in handling MaF8's complex and disconnected Pareto landscape.

Other Metrics: For metrics like CPF, DM, DeltaP, HV, IGD, IGDp, PD, and Spacing, no statistically significant differences were observed. This suggests that in that both algorithms have similar performance in terms of overall diversity and coverage. However, it is worthwhile to note that pointing out that MOBCA demonstrated a greater standard variations, particularly in IGD and DeltaP, which suggests that there may be inconsistency in performance because it's hard to deal with the disconnected the characteristics of the Pareto front of MaF8.

These findings emphasize how crucial it is to comprehend the algorithm's strength in the context of optimization. Scenarios requiring accuracy are better suited to the LMPFE. whereas convergence is more suited for MOBCA. Applications requiring quick computation and a wide range of answers take precedence.

C. Comprehensive Performance

LMPFE demonstrates superior performance over MOBCA in terms of convergence, particularly in the Generational Distance (GD) metric, where it achieves significantly lower values, indicating closer proximity to the optimal Pareto front. This suggests LMPFE is more effective for applications requiring high-precision convergence in complex search spaces like MaF8. Its performance may be attributed to its enhanced feature extraction strategy, which aids in better exploration and exploitation.

On the other hand, MOBCA shows strengths in runtime efficiency, achieving faster execution times, and also maintains a competitive spread of solutions. These characteristics make MOBCA more suitable for scenarios where computational speed and solution diversity are prioritized.

In conclusion, the selection between LMPFE and MOBCA should be guided by the specific goals of the optimization task—LMPFE for convergence-focused applications and MOBCA for diversity and speed.

D. Qualitative Insights

The observed trade-off between convergence and diversity is a central theme in many-objective optimization. MaF8's irregular and disconnected Pareto front creates a challenging landscape for MOEAs, where algorithms must balance between converging to optimal regions and maintaining diversity. MOBCA's broader spread and faster runtime make it effective in exploring diverse regions, but its convergence is less consistent. LMPFE, in contrast, sacrifices some diversity for more reliable convergence, which can be advantageous in constrained or precision-critical applications.

E. Impact of MaF8's Characteristics

MaF8 poses a significant challenge due to its two-dimensional decision space coupled with 10 objectives, resulting in a high-dimensional, irregular Pareto front. The disconnected nature of the front makes it difficult for exploration-based algorithms like MOBCA to maintain consistency across runs. This leads to high variability in certain metrics. In contrast, LMPFE's feature extraction strategy effectively reduces the complexity of the decision space, enabling it to maintain stability and accuracy in convergence. This suggests that the success of an MOEA may depend not only on its operators but also on its ability to adapt to the structural characteristics of the problem.

F. Practical Implications

These findings hold valuable implications for many-world applications such as structural design, hyperparameter optimization in machine learning, and resource allocation. In domains where obtaining an accurate approximation of the Pareto front is critical, LMPFE would be more appropriate. However, in dynamic or large-scale environments where speed and diversity are more important, MOBCA's strengths could offer practical advantages. Selecting the right algorithm, therefore, hinges on clearly defining the optimization goals and understanding the nature of the problem's objective space.

V. CONCLUSION AND FUTURE WORK

Using the effectiveness of PlatEMO architecture further studies was evaluated on numerous objective optimization techniques, like MOBCA an LMPFE—on the MaF8 benchmark issue, utilizing the PlatEMO architecture [26]. The findings emphasize that major variations persist that known to be more proactive in this overall approach like evolutionary multi-objective improvement.

LMPFE demonstrated superior performance in terms of convergence, evidenced by a notably lower Generational Distance (GD) value. This indicates its enhanced ability to approximate the true Pareto front accurately. Its feature extraction mechanism, as discussed in [27], likely simplifies the search space, enabling more efficient and accurate convergence even in problems with irregular or disconnected Pareto fronts, such as MaF8. This leads to higher efficiency and precision in convergence, even for complex problems with irregular or disconnected Pareto fronts like MaF8. Its consistent performance is another key strength. Additionally, its practical value is evident from its runtime, making it particularly useful in scenarios where solution accuracy and stability are critical—such as in structural engineering design, machine learning, or hyperparameter tuning [23].

On the other hand, MOBCA performed admirably in terms of runtime, spread and performance, which point to its benefits in computational efficiency and a range of solutions. Its features make it ideal for real-time systems, big applications with scale issues or those that need a wide variety of trade-offs. But its, as demonstrated in [28], The performance was less consistent, especially in DeltaP and maybe because of challenges in handling IG data the disconnected Pareto fronts, which are typical of The issue with MaF8 [26].

These findings reaffirm that algorithm selection must align with problem-specific optimization goals. For problems where precision, convergence, and reliability are prioritized, LMPFE stands out as the preferred option. On the other hand, MOBCA is more appropriate for problems that demand speed and diversity, where a wide exploration of the solution space is essential.

In the future, studies may concentrate on creating hybrid frameworks that combine the convergence capacity of LMPFE with the diversity and speed of MOBCA. Multiphasic optimization, ensemble-based MOEAs, or cooperative coevolutionary algorithms are examples of strategies that may offer a fair balance between performance [29]. Furthermore, additional research into how benchmark features like objective dimensionality, decision space structure, and front modality affect algorithm behavior will be crucial for creating resilient and adaptive MOEAs [30].

Furthermore, algorithms may dynamically switch between exploration and exploitation, increasing robustness across various problem landscapes by incorporating adaptive learning methods, such as feedback-driven operator adaptation or reinforcement learning-based strategy selection [31]. In complicated real-world fields where optimization under uncertainty and complexity is commonplace, such as autonomous systems, intelligent manufacturing, and multi-objective control systems, these advancements may have significant consequences.

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