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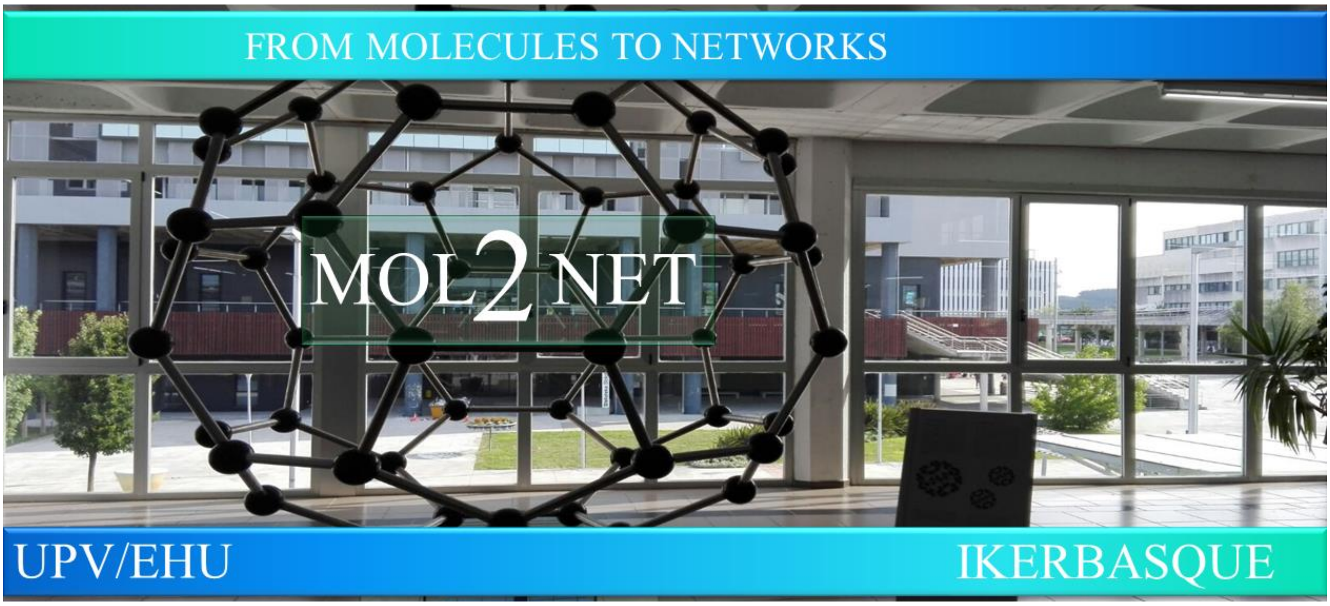

Selective Pressure through Differential Evolution and Decomposition in Multi-Objective Simulated Annealing

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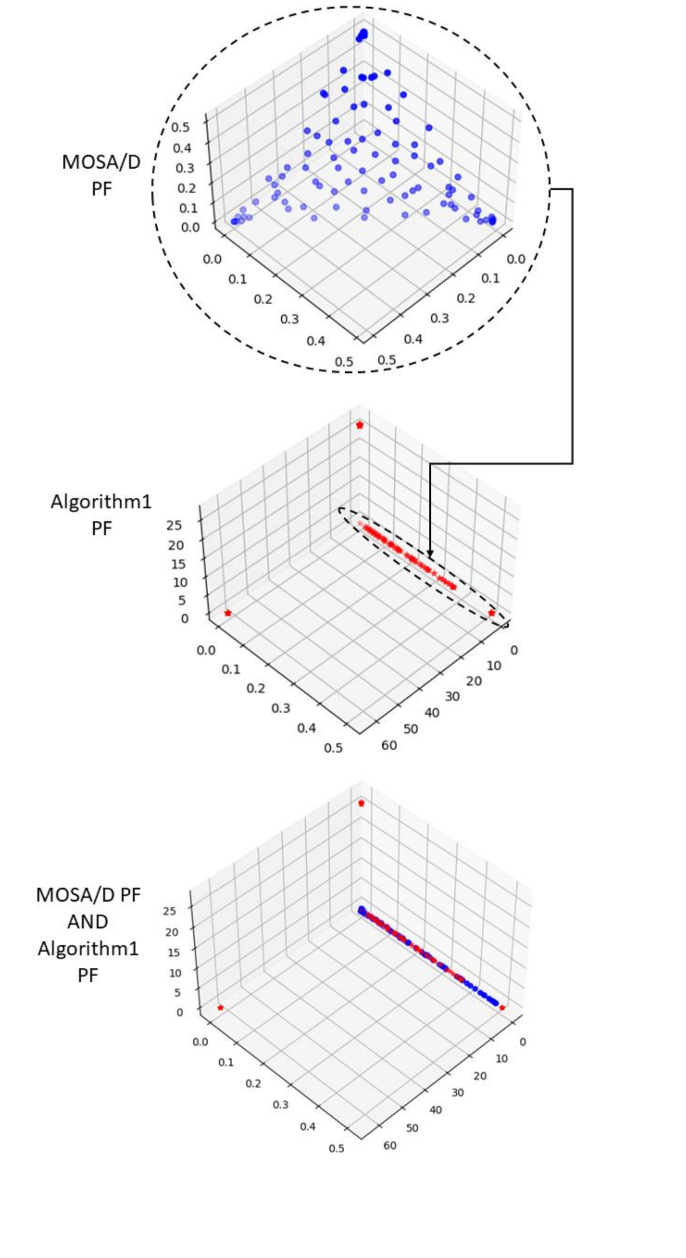
Graphical Abstract	**Abstract.**
	In the real world, optimization problems have multiple objectives that usually are in conflict. Traditionally the Pareto-based approach has been applied to Multi-Objective Optimization Problems (MOPs). But this strategy has a limitation: The increment in the number of objectives produces issues. Such as the



deterioration of the searchability of the algorithm. It reduces the selective pressure on the Pareto Front (PF). To address this problem, we propose an algorithm called MOSA/D. MOSA/D is a Multi-Objective Simulated Annealing (MOSA) strategy based on Decomposition (D) and Differential Evolution (DE). Decomposition divides a MOP into sub-problems that can be optimized almost in a classical sense, like single-optimization problems. With this idea, in MOSA/D, each sub-problem is annealed to find its optimal solution. During this annealing process, Differential Evolution produces candidate solutions to be evaluated by aggregation and probability functions. Simulated Annealing adds exploration and exploitation to each sub-problem while decomposition strategy and differential evolution operators reduce the lack of selective pressure toward the PF. MOSA/D is compared to MOEA/D to prove the performance of the algorithm. The experimental design used the DTLZ benchmark. In particular, the problems DTLZ1, DTLZ2, and DTLZ3 with five objectives. Experimental results show that MOSA/D outperforms or performs similarly to MOEA/D. These results are in terms of the mean and standard deviation from Hypervolume (HV) and Inverted Generational Distance (IGD).

Introduction

In the real world, optimization problems have multiple objectives that usually are in conflict. Traditionally the Pareto-based approach has been applied to Multi-Objective Optimization Problems (MOPs). But this strategy has a limitation: The increment in the number of objectives (objective scalarization) produces issues. Such as deterioration of the searchability of the algorithm. Due to that, almost all solutions found are non-dominated (Ishibuchi et al., 2008). It reduces the selective pressure on the Pareto Front (PF). For example, NSGA-II and SPEA are algorithms based on Pareto dominance that have problems with a large number of objectives.

To address objective scalarization, we introduce a strategy to solve Multi-Objective Optimization Problems in this work. The main idea is to divide a MOP into sub-problems like single-optimization problems using Decomposition. Then must be applied two strategies: Simulated Annealing (SA) and Differential evolution (DE). SA adds exploration and exploitation to each sub-problem. While exploration introduces new information about each sub-problem, exploitation takes advantage of that information. DE is a state-of-the-art global optimization technique (Opara & Arabas, 2019). This evolutionary algorithm differs from others in its mutation operator. It mutates the base vectors with scaled population-derived difference vectors, and as generations pass, these differences tend to adapt to the natural scaling of the problem (Opara & Arabas, 2019). Decomposition and Differential Evolution alleviates the lack of selective pressure toward the PF while SA works to find the optimum for each sub-problem.

Materials and Methods

The Multi-Objective Simulated Annealing based on Decomposition (MOSA/D) takes a multi-objective optimization problem (MOP) to decompose it into a set of N sub-problems, represented by a set of N weight vectors (v). Then the sub-problem v_i is associated with a unique solution Pi from the population P. The algorithm works as follows: while the temperature T is less than Tf, each sub-problem will be annealed for L executions at a temperature level of T. For each L execution, a candidate solution will be obtained (Scand) by Differential Evolution perturbation (mutation and crossover operations) of $S_{current}$. S_{cand} must be evaluated and compared with Pi (associated with the i-th sub-problem) in terms of the Tchebycheff function. S_{cand} must be compared with $S_{current}$ to update $S_{current}$ in the next step. If the comparison is not in favor of $_{Scand}$, the Boltzmann probability can be applied (like classical SA, Amine 2019). Finally, for each temperature level of T, this process will occur for N × L executions. The MOSA/D algorithm proposed is shown in figure 1.

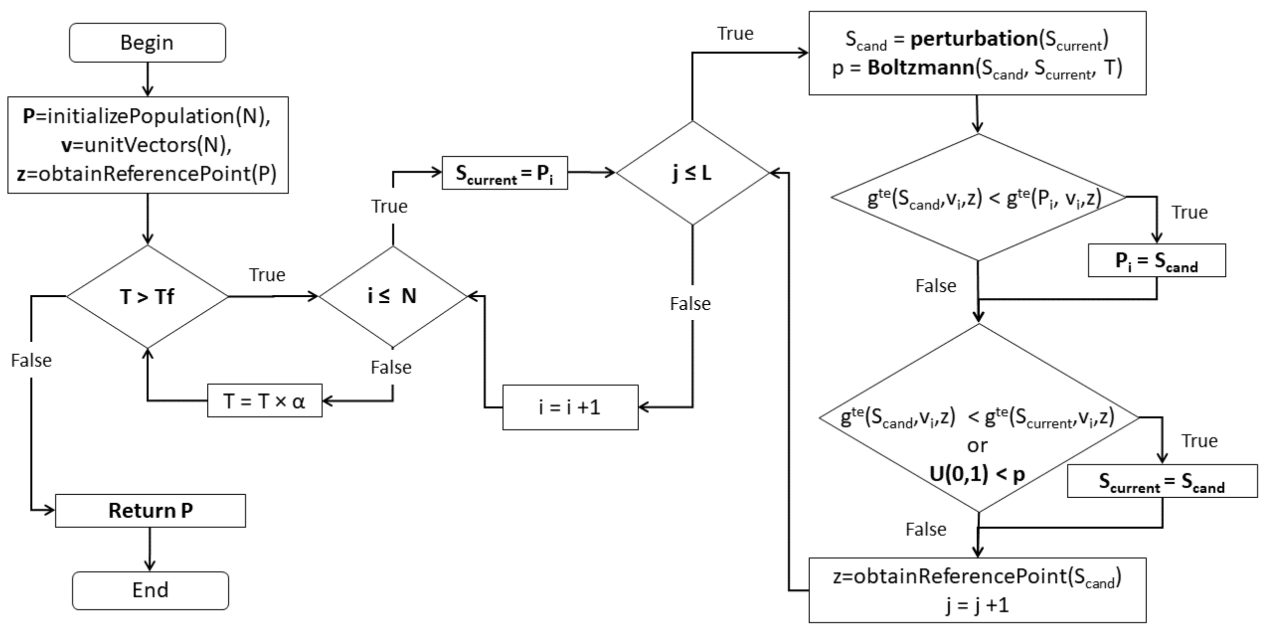


Figure 1. Flowchart of MOSA/D main algorithm

Results and Discussion

MOSA/D is compared to MOEA/D to prove the performance of the algorithm. The experimental design used the DTLZ benchmark. In particular, the problems DTLZ1, DTLZ2, and DTLZ3 with five objectives. The results are in terms of the mean and standard deviation from Hypervolume (HV) and Inverted Generational Distance (IGD). Generally, the HV and the IGD are two widely used metrics to measure the performance of MOEAs in terms of both convergence and diversity (Chen et al., 2019). The experimental design for the MOSA/D is shown in table 1.

Table 1. Experimental design of MOSA/D and MOEA/D

Algorithm	MOSA/D, MOEA/D
indicators	Hypervolumen (HV), Inverted Generational Distance (IGD)
Standard Problem	DTLZ1, DTLZ2, DTLZ3
Number of objectives	5
Size of population	100
Number of evaluations	100000
Runs by variant	30

The HV (table 2) shows the results are promising in favor of MOSA/D over MOEA/D for five objectives on DTLZ2 and DTLZ3. With DTLZ1 on average, there is a similar performance of MOSA/D and MOEA/D, but the standard deviation of MOSA/D shows more stable results.

Table 2. Mean and Standard Deviation from HV results from 30 runs by experiment

Problem	M	MOEA/D	MOSA/D
DTLZ1	5	7.289E+11 (3.14E+07)	7.289E+11 (5.767E+04)
DTLZ2	5	2.196E+02 (1.015E+00)	2.205E+02 (6.450E-02)
DTLZ3	5	8.037E+14 (5.730E+11)	8.038E+14 (9.481E+08)

The IGD (Table 3) shows the results are promising in favor of MOSA/D over MOEA/D for five objectives on all problems (DTLZ1, DTLZ2, and DTLZ3). Also, the standard deviation of MOSA/D shows more stable results.

Table 3. Mean and Standard Deviation from IGD results from 30 runs by experiment

Problem	M	MOEA/D	MOSA/D
DTLZ1	5	9.343E-01 (1.359E-01)	1.359E-01 (9.388E-03)
DTLZ2	5	5.390E-01 (2.664E-02)	4.361E-01 (1.591E-02)
DTLZ3	5	1.934E+01 (1.620E+01)	4.599E+00 (1.450E+00)

Conclusions

This document introduces the algorithm MOSA/D which is a Multi-Objective Simulated Annealing Based on Decomposition and Differential Evolution;
While Simulated Annealing adds exploration and exploitation to each sub-problem to find its optimal solution, Differential Evolution and Decomposition add to the algorithm selective pressure toward the PF;
The tests for DTLZ1, DLTZ2, and DTLZ3 with five objectives show results (HV and IGD) in favor of MOSA/D over MOEA/D in terms of convergence and diversity;
The standard deviation in both indicators (HV and IGD) shows stability in favor of the MOSA/D algorithm;
The results are promising, so it would be relevant to prove some configurations and variants of MOSA/D in future experiments. For example
i) a variant using classical genetic operators (SBX and polynomial mutation);
ii) a configuration with ten and twenty objectives;
iii)a variant that uses the concept of the neighborhood like in MOEA/D (Zhang et al., 2007).

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