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Experimental Analysis of a Cooperative Coevolutionary Algorithm with Parameter Tuning for Multi-objective Problem Optimization with Uncertainty

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Abstract. Currently, organizations face significant challenges demanding effective and efficient solutions. The problem optimization and decision-making coupled with Decision Maker Preferences (DMPs), are crucial for achieving success and maintaining a competitive edge. In many cases, business problems involve the need to optimize multiple conflicting objectives, and DMPs may not be entirely precise. Coevolutionary algorithms have become increasingly popular as effective tools for solving problems involving multiple objectives. These techniques enable the simultaneous evolution of multiple solutions through the interaction and joint improve of different populations. Coevolutionary algorithms promote cooperative solution improvement, fostering diversity and facilitating the discovery of optimal solutions to complex problems. Parameter tuning is critical in coevolutionary algorithms as it determines how potential solutions are explored and enhances their ability to avoid local optima, directing the search toward global solutions. In this article, an analysis is conducted to identify the most viable configurations using parameter tuning in a cooperative coevolutionary algorithm to solve multi-objective problems with uncertainty. Experimental results demonstrate that no configuration dominates by absolute distance, but options are identified that can generate high-quality solutions.

Keywords. Parameter tuning, cooperative coevolution algorithm, multi-objective problem optimization.

1 Introduction

In business, scientific, and everyday life contexts, optimizing multi-objective problems has become a challenge spanning various disciplines, from engineering to decision-making in daily situations. In a world where efficiency is essential for success and competition is ever-increasing, the ability to optimize solutions that align with individual preferences, even when these preferences involve imprecise values.

Decision-making, as emphasized by Koziol [1], is one of the most critical processes in managing modern organizations due to its direct impact on the success or failure of the organization.

This aspect becomes even more relevant in environments characterized by uncertainty in information, where understanding the factors influencing decision-making is crucial for tackling challenges in problems. Currently, to address problems such as many-objective optimization problems (MaOP), coevolutionary strategies have been applied.

An example of this, is the work of Li et al. [2], who propose a cooperative coevolutionary algorithm with a dynamic learning strategy to solve

MaOP, called Dynamic Learning Cooperative Coevolutionary Algorithm of Two Populations (DL-TPCEA). In this work, they use only two populations to exchange information with evolution based on two criterias: one population uses the Pareto criterion (PC) and the other uses the non-Pareto criterion (NPC). Parameter tuning is performed only for the maximum number of iterations, the number of objectives, the diversity value, and the strategy of division in the coevolutionary approach by objectives.

On the other hand, coevolutionary strategies have also been employed to solve large-scale multi-objective optimization problems (LSMOP), such as in the work of Zhong, et al. [3], who proposed a cooperative coevolutionary algorithm using hybrid NSGA-II with Linkage Measurement Minimization (CC-HNSGA-LMM).

They apply an elitist genetic algorithm for the problem decomposition stage, then they move to an optimization stage and introduce the best-generated solution into the cooperative coevolutionary algorithm, employing a variable clustering method for LSMOP, aiming to improve solutions around the Pareto Front.

In this work, parameter adjustment is used in the clustering stage: the population size is 20, the maximum set of iterations is 20, and the gene size (number of clusters) is 6 and 7. They also perform parameter adjustments for subproblem optimization: dimensions of 500D and 1000D. Besides adjusting their genetic operators.

Upon analysis, similarities were found between the reviewed works and ours, such as the use of coevolutionary algorithms. However, unlike our work, they [2, 3] use the Pareto Front, whereas we address the Region of Interest (ROI). The ROI represents a set of solutions that are DMP, where we apply values with uncertainty to the DMP, allowing a range of values in these preferences.

Additionally, instead of finding a ROI, our approach generates a set of them. Furthermore, these works also employ parameter tuning, but with a different focus. In these works, parameter adjustment focuses on genetic operators such as crossover and mutation, whereas our approach focuses on configuring the number of species, the species division strategy (by variables and objectives), and the number of variables and objectives per species.

Until this date, classic evolutionary algorithms configure parameters of genetic operators such as crossover, mutation, and selection [3][4]. However, when addressing an evolutionary algorithm, they tend to propose a specific design in the values of their parameters, without considering small variations in them.

This research conducts a study on the impact on the quality of solutions to multi-objective problems when applying different coevolutionary designs. The results demonstrate that the parameters of coevolutionary design indeed have an impact on the quality of solutions and should be considered in the problem-solving process.

The contribution of this work is a methodology for designing coevolutionary algorithms, which is based on the configuration of three parameters: 1) the number of species, 2) the division strategy (by objectives or variables), and 3) the number of variables and objectives per species.

This article consists of the following sections: Section 2 provides general information, including a description of multi-objective optimization under uncertainty, a definition of the coevolutionary algorithm, and a description of the cooperative coevolutionary approach by Potter and De Jong [5], as well as details on parameter tuning. Section 3 addresses the solution methodology, while Section 4 describes the experimental design. The results of the experimentation are discussed in Section 5, and finally, a general conclusion is presented in Section 6.

2 Background

2.1 Multi-objective Optimization with Uncertainty

Within the realm of multi-objective optimization, the fundamental task is to determine values for a set of decision variables that satisfy constraints while optimizing a vectorial function [6]. This vectorial function is composed of elements representing individual objective functions, which offer a mathematical representation of various performance criteria that often conflict with each other. Multi-objective optimization aims to find a solution that provides acceptable values for all objective functions for the decision-maker.

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This approach seeks to reconcile objectives and constraints, considering potential contradictions among the stated objectives [7, 8]. Precise mathematical formulation is crucial to address this challenge and reflect the complexity of optimization criteria and involved constraints (Eq. 1).

The decision-maker (DM) can express each objective as an interval, considering imprecision, that is, $f_j(x) = \left[\underline{f_j}(x), \overline{f_j}(x)\right]$Each element of the set X is treated as a vector of intervals $\vec{f}(x)$:

$$\begin{gathered} max\ F(x) = (f_1, f_2, \ldots, f_m) \\ \text{Subject to: } x \in \Omega. \end{gathered} \tag{1}$$

Uncertainty arises from incomplete knowledge. Representing objectives as intervals reflect the imprecision associated with the goals, enabling greater flexibility in decision-making in the face of uncertainty. This approach incorporates the inherent variability in the decision-making process and enhances the model's ability to adapt to situations where available information may be imprecise.

2.2 Coevolutionary Algorithm

Coevolution represents a process through which two or more species interact mutually and undergo evolutionary changes in response to adaptations observed in each other. This concept originates from the principles of Charles Darwin in 1859, where the notion of evolution was introduced [9].

Within coevolutionary algorithms, two predominant approaches are distinguished: cooperation and competition. In the cooperative approach, populations work together to enhance overall performance [10], whereas in the competitive approach, populations compete to gain advantages over other populations. This research work uses a cooperative approach as the central focus of the study.

2.3 Cooperative Coevolutionary Approach

In 1994, Potter and De Jong introduced the technique of cooperative coevolution (Fig. 1) to address challenges in function optimization [5]. This strategy involves decomposing the objective function into several sub-functions, allowing the evolution of independent solutions for each of them. Subsequently, these solutions are combined into a complete solution.

Cooperative coevolution directs the evolutionary process towards more manageable subproblems, avoiding to get trapped in the local optima of the global function.

Furthermore, it promotes learning among solutions, resulting in continuous performance improvement over time. Currently, numerous research studies have successfully implemented coevolution in algorithms to address a variety of challenges. These studies have highlighted the potential of coevolutionary algorithms in solving complex problems in diverse fields such as engineering, optimization, and decision-making, among others [2, 11, 12].

Despite their advantages, it is crucial to remember that achieving successful results in coevolutionary algorithms largely depends on the configuration of their parameters. Adjustment parameters, such as population size, mutation and crossing rate, and the number of generations provide a critical factor to achieve efficient performance and obtain high quality solutions. Bad parameter options could lead to premature convergence or insufficient diversity in the quality of solutions.

3 Methodology

The Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) along with its various variants from VAR1 to VAR6 proposed by Fernandez, et al. [13] has been incorporated into a cooperative coevolutionary algorithm. The design of Fernandez's algorithm [14] is aimed at addressing the imprecision present in the data used by the DM by incorporating interval-based models and dominance relationships. The variants introduce modifications to the Tchebychev scalar function of the MOEA/D to integrate dominance relationships into the evolutionary search process.

Mejía [15] identifies two perspectives in parameter tuning: the "online" approach, where values are dynamically updated during algorithm execution, and the "offline" approach, where it is done before algorithm execution.

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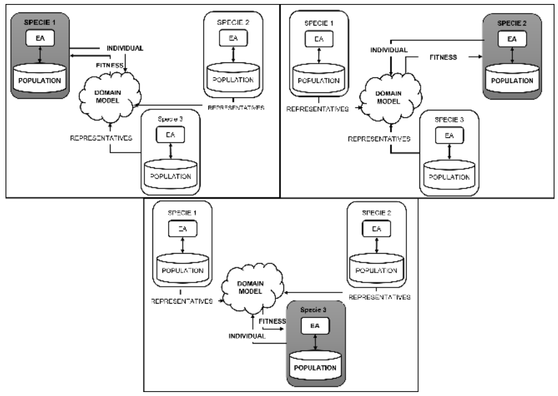

Fig. 1. Coevolutionary model of three species shown from the perspective of each in turn [5]

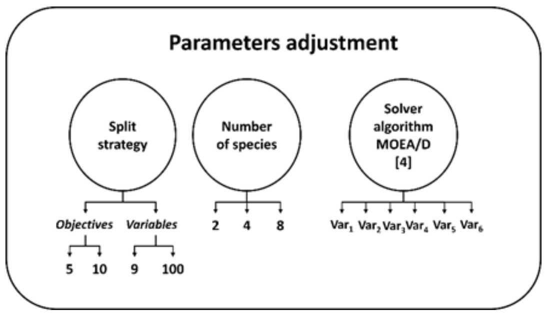

Fig. 2. Cooperative coevolutive parameter adjustment

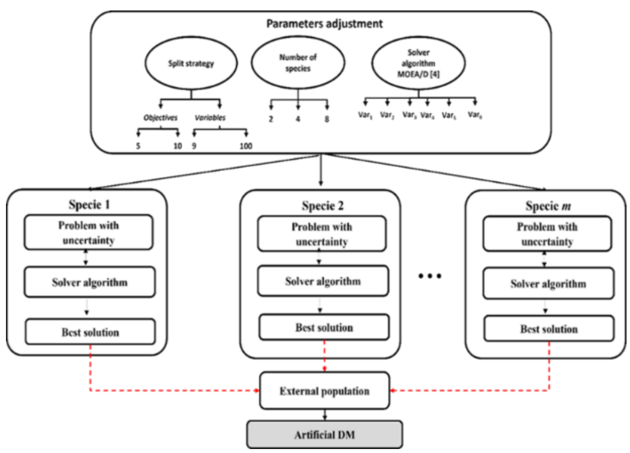

Fig. 3. Cooperative coevolutive algorithm with uncertainty

Parameter tuning is crucial as it significantly contributes to the efficiency and effectiveness of the optimization process, allowing for high-quality results in solution search.

In Fig. 2, different parameters adjusted in the coevolutionary algorithm can be observed, such as the split strategy which can be based on objectives or variables, the number of species the algorithm will work with, and the solving algorithm for the species.

Fig. 3 illustrates the cooperative coevolutionary algorithm, where parameter tuning is done offline, as it takes place before the coevolutionary process begins.

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Table 1. Experimental design of coevolutionary algorithms

Algorithm	**Variant**	**Split strategy**
Coevolutionary 1		2 objectives
Coevolutionary 2		4 objectives
Coevolutionary 3	MOEA/D	2 variables
Coevolutionary 4		4 variables
Coevolutionary 5		8 variables
Coevolutionary 6		2 objectives
Coevolutionary 7		4 objectives
Coevolutionary 8	VAR1	2 variables
Coevolutionary 9		4 variables
Coevolutionary 10		8 variables
Coevolutionary 11		2 objectives
Coevolutionary 12		4 objectives
Coevolutionary 13	VAR2	2 variables
Coevolutionary 14		4 variables
Coevolutionary 15		8 variables
Coevolutionary 16		2 objectives
Coevolutionary 17		4 objectives
Coevolutionary 18	VAR3	2 variables
Coevolutionary 19		4 variables
Coevolutionary 20		8 variables
Coevolutionary 21		2 objectives
Coevolutionary 22		4 objectives
Coevolutionary 23	VAR4	2 variables
Coevolutionary 24		4 variables
Coevolutionary 25		8 variables
Coevolutionary 26		2 objectives
Coevolutionary 27		4 objectives
Coevolutionary 28	VAR5	2 variables
Coevolutionary 29		4 variables
Coevolutionary 30		8 variables
Coevolutionary 31		2 objectives
Coevolutionary 32		4 objectives
Coevolutionary 33	VAR6	2 variables
Coevolutionary 34		4 variables
Coevolutionary 35		8 variables

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Having the parameter values, the problem is divided among the number of species, with each species working on the respective objectives or variables to evolve. It then moves to the solving algorithm, which receives the species to work with and generates a population subjected to mutation and crossover operators.

Consequently, each species selects a representative, which is the best solution of the species. In the end, each species cooperates with each other, forming complete solutions stored in the external populations (EP).

4 Experimental Design

DTLZ1-7 and WFG1-9 are benchmark problems that have been used to assess the performance of MOEA/D with preferences. The number of objectives used in this study was m = {5, 10} and the number of variables used was k= {9,100}.

4.1 Parameters Tuning

When addressing real-world problems, it is common to use algorithms that require specific configurations to ensure competitive performance. The quality of an algorithm is closely linked to the values of its parameters, posing a crucial challenge in various fields. In his article, Ocaño et al. [16] point out the No Free Lunch (NFL) theorem, which states that there is no set of optimal parameters that can solve all optimization problems.

Therefore, parameter tuning is essential for algorithm performance, requiring careful selection of values to guide its behavior and performance.

In the context of coevolutionary algorithms, this process involves selecting appropriate values for specific elements such as configuring the number of species, the species division strategy (by variables and objectives), and the number of variables and objectives per species.

In this study, we focus on offline parameter tuning, where the configuration is established before the algorithm execution, recognizing the importance of this phase in obtaining effective results in real-world problems.

Table 2. Results of best parameter configurations for problems with five and ten objectives

No. objectives	Variant	Split strategy	No. species
5	VAR_2	Variables	4
	VAR_6	Variables	4
10	VAR_6	Objectives	4
	VAR_4	Variables	4

4.2 Quality Measures

Quality measures, also known as metrics or indicators, play a fundamental role in evaluating the efficiency and performance of algorithms, especially in the context of optimization. In the study by Castellanos [17], it is noted that while traditional metrics such as hypervolume, spacing, and dispersion exist, these may be insufficient when evaluating preference-based algorithms.

In that work, the use of distance-based indicators to measure quality in terms of similarity between the optimal set $X^*$and the Approximation to the Region of Interest (A-RoI) is proposed. The minimum Euclidean distance and the minimum Tchebychev distance are used to calculate the proximity of the A-RoI to the nearest point in X^*.

Additionally, the average of minimum Euclidean distance and the average of minimum Tchebychev distance are introduced, representing the average distance from points in the A-RoI to those in X^*. Furthermore, the median Euclidean and median Tchebychev are considered, reflecting the median distances from the A-RoI to the nearest point in X^*.

Each of these metrics underwent the Borda Count method to determine the best configuration according to the DMPs. This voting method assigns scores to options based on their ranking by each voter. The steps to perform the Borda Count are as follows:

1 **Assigning Scores**: Each candidate receives a score based on their position in each preference list. The most preferred candidate in a list receives the highest score, and scores decrease as you move down the list.

2 **Assigning Scores to Preferences:** A specific score is assigned to each position in the

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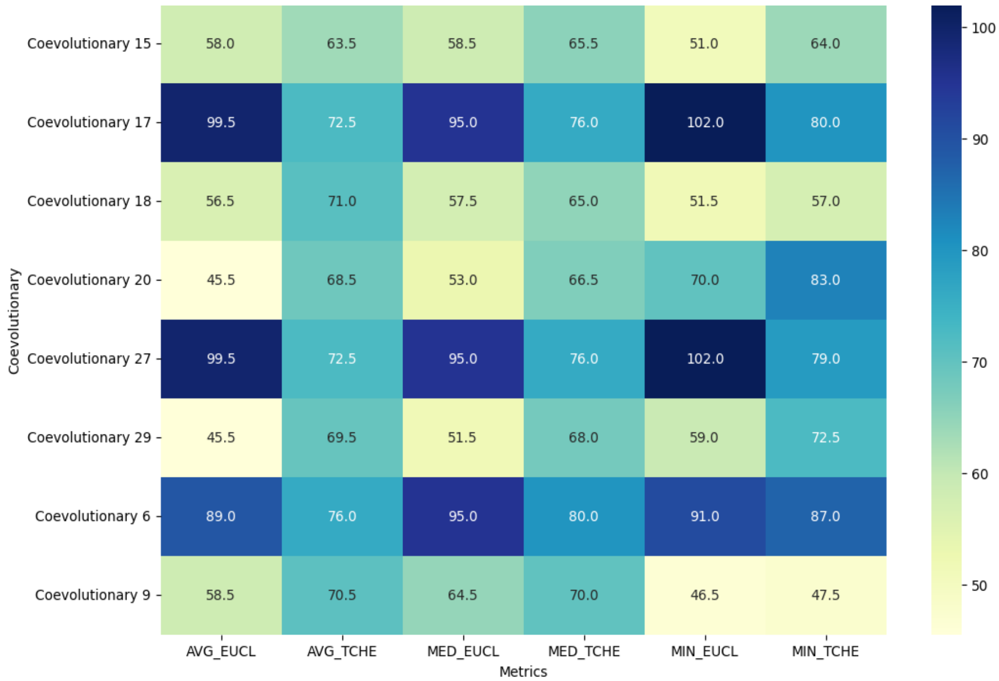

Fig. 4. Counting summary of algorithms with good performance on five objective problems

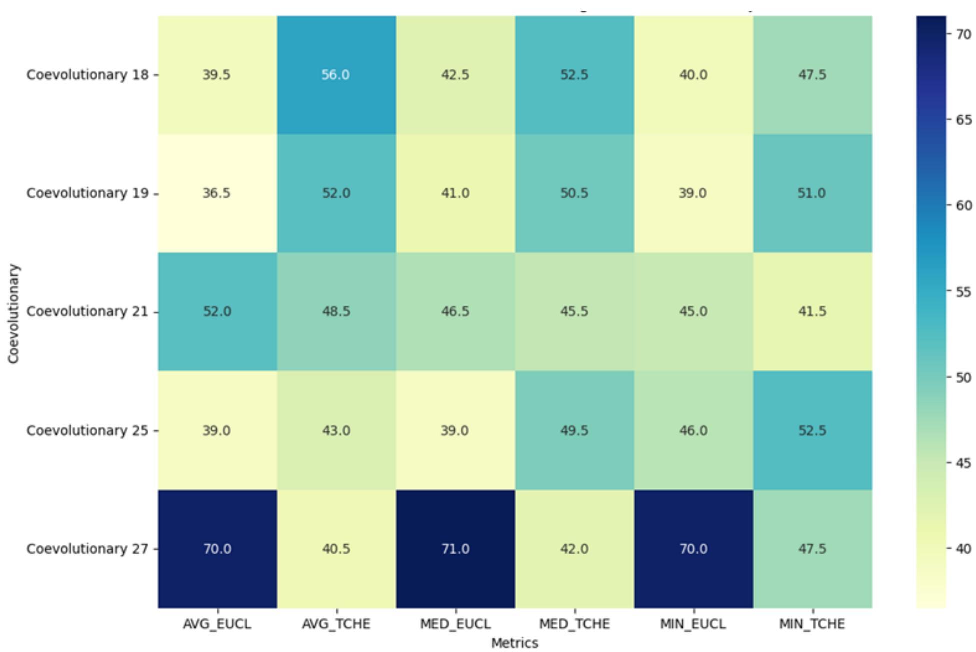

Fig. 5. counting summary of algorithms with good performance on ten objective problems

preference list. For example, if there are n candidates, the most preferred candidate in a list may receive n points, the next one $n-1$ points, and so forth.

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Table 3. Ranking of problem with five objectives, division of objectives and two species

	PROBLEM	VARIANT	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
PROBLEMS WITH FIVE OBJECTIVES. DIVISION BY OBJECTIVES AND TWO SPECIES	**DTLZ1**	MOEA/D	4	5	5.5	5	5	5
		VAR_1	1	1.5	1	1.5	1	1
		VAR_2	4	5	5.5	5	5	5
		VAR_3	6.5	5	5.5	5	5	5
		VAR_4	2	1.5	2	1.5	2	2
		VAR_5	6.5	5	5.5	5	5	5
		VAR_6	4	5	3	5	5	5
	DTLZ2	MOEA/D	6	6	4	6	6	4.5
		VAR_1	3	2.5	4	3	2.5	4.5
		VAR_2	6	6	4	6	6	1
		VAR_3	3	2.5	4	3	2.5	4.5
		VAR_4	3	2.5	4	3	2.5	4.5
		VAR_5	1	2.5	4	1	2.5	4.5
		VAR_6	6	6	4	6	6	4.5
	DTLZ3	MOEA/D	3	6	3	6	3	2.5
		VAR_1	3	2.5	3	1	3	2.5
		VAR_2	3	2.5	3	3	3	2.5
		VAR_3	6.5	6	6.5	6	6.5	6.5
		VAR_4	3	2.5	3	3	3	2.5
		VAR_5	6.5	6	6.5	6	6.5	6.5
		VAR_6	3	2.5	3	3	3	5
	DTLZ4	MOEA/D	3	6	4.5	6	3	4.5
		VAR_1	6.5	2.5	1	2.5	6.5	1
		VAR_2	3	6	4.5	6	3	4.5
		VAR_3	3	2.5	4.5	2.5	3	4.5
		VAR_4	6.5	2.5	4.5	2.5	6.5	4.5
		VAR_5	3	2.5	4.5	2.5	3	4.5
		VAR_6	3	6	4.5	6	3	4.5
	DTLZ5	MOEA/D	7	2	6	2	7	7
		VAR_1	3.5	5.5	3.5	5.5	3.5	3.5
		VAR_2	3.5	2	6	2	3.5	3.5
		VAR_3	3.5	5.5	3.5	5.5	3.5	3.5
		VAR_4	3.5	5.5	1.5	5.5	3.5	3.5
		VAR_5	3.5	5.5	1.5	5.5	3.5	3.5
		VAR_6	3.5	2	6	2	3.5	3.5
	DTLZ6	MOEA/D	5	5	5	2	4	4
		VAR_1	1.5	5	1.5	5.5	4	4
		VAR_2	5	1.5	5	2	4	4
		VAR_3	5	5	5	5.5	4	4
		VAR_4	1.5	5	1.5	5.5	4	4
		VAR_5	5	5	5	5.5	4	4
		VAR_6	5	1.5	5	2	4	4
	DTLZ7	MOEA/D	4	1	1	1	4	4
		VAR_1	4	5.5	4.5	5.5	4	4
		VAR_2	4	1	4.5	3	4	4
		VAR_3	4	5.5	4.5	5.5	4	4
		VAR_4	4	5.5	4.5	5.5	4	4
		VAR_5	4	5.5	4.5	5.5	4	4
		VAR_6	4	1	4.5	2	4	4

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WFG1	MOEA/D	3	5.5	6	6	3	6
	VAR_1	3	1	2.5	2.5	3	2.5
	VAR_2	3	1	6	6	3	6
	VAR_3	6.5	5.5	2.5	2.5	6.5	2.5
	VAR_4	3	1	2.5	2.5	3	2.5
	VAR_5	6.5	5.5	2.5	2.5	6.5	2.5
	VAR_6	3	5.5	6	6	3	6
WFG2	MOEA/D	5.5	4	1	4	6	2
	VAR_1	2.5	4	6	4	4	5.5
	VAR_2	5.5	4	2.5	4	6	2
	VAR_3	5.5	4	6	4	2	5.5
	VAR_4	1	4	4	4	2	5.5
	VAR_5	2.5	4	6	4	2	5.5
	VAR_6	5.5	4	2.5	4	6	2
WFG3	MOEA/D	6	5	5	4.5	6	5
	VAR_1	2.5	1.5	5	1	2	5
	VAR_2	6	5	5	4.5	6	5
	VAR_3	2.5	5	1.5	4.5	2	2
	VAR_4	2.5	1.5	5	4.5	4	5
	VAR_5	2.5	5	1.5	4.5	2	1
	VAR_6	6	5	5	4.5	6	5
WFG4	MOEA/D	6	6	2	6	6	2
	VAR_1	2.5	2.5	5.5	3.5	3	5.5
	VAR_2	6	6	2	6	6	2
	VAR_3	2.5	2.5	5.5	2	3	5.5
	VAR_4	2.5	2.5	5.5	3.5	3	5.5
	VAR_5	2.5	2.5	5.5	1	1	5.5
	VAR_6	6	6	2	6	6	2
WFG5	MOEA/D	3	6	6	6	3	6
	VAR_1	3	2.5	2.5	2.5	3	4
	VAR_2	6.5	6	6	6	6.5	6
	VAR_3	3	2.5	2.5	2.5	3	2
	VAR_4	3	2.5	2.5	2.5	3	2
	VAR_5	3	2.5	2.5	2.5	3	2
	VAR_6	6.5	6	6	6	6.5	6
WFG6	MOEA/D	5.5	5.5	4.5	5	5	4.5
	VAR_1	5.5	5.5	4.5	5	5	4.5
	VAR_2	5.5	5.5	4.5	5	5	4.5
	VAR_3	2	2	4.5	2	1.5	4.5
	VAR_4	3	2	4.5	5	5	4.5
	VAR_5	1	2	1	1	1.5	1
	VAR_6	5.5	5.5	4.5	5	5	4.5
WFG7	MOEA/D	6	6	6	6	6	6
	VAR_1	3	4	2.5	2.5	3	2.5
	VAR_2	6	6	6	6	6	6
	VAR_3	2	1	2.5	2.5	2	2.5
	VAR_4	4	1	2.5	2.5	4	2.5
	VAR_5	1	1	2.5	2.5	1	2.5
	VAR_6	6	6	6	6	6	6
WFG8	MOEA/D	6	6	4	6	6	4
	VAR_1	2.5	2.5	4	2.5	3.5	4
	VAR_2	6	6	4	6	6	4
	VAR_3	2.5	2.5	4	2.5	3.5	4
	VAR_4	2.5	2.5	4	2.5	1.5	4
	VAR_5	2.5	2.5	4	2.5	1.5	4
	VAR_6	6	6	4	6	6	4
WFG9	MOEA/D	4.5	4.5	4	4	5	4
	VAR_1	1	4.5	4	4	1	4
	VAR_2	4.5	4.5	4	4	5	4
	VAR_3	4.5	4.5	4	4	5	4
	VAR_4	4.5	4.5	4	4	2	4
	VAR_5	4.5	1	4	4	5	4
	VAR_6	4.5	4.5	4	4	5	4

3 **Summing Scores:** The scores for each candidate from all lists are added. The candidate with the highest total score is considered the winner if the problem is a maximization problem, but if it is a minimization problem, the candidate with the lowest total score is considered the winner.

Table 4. Borda count of coevolutionary with objective division and two species

VARIANTE	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
MOEA/D	77.5	79.5	67.5	75.5	78	71
VAR1	48	53	55	52	52	58
VAR2	77.5	68	72.5	74.5	78	64
VAR3	62.5	61.5	66.5	59.5	57	64.5
VAR4	49.5	46.5	55.5	57.5	53	60.5
VAR5	55.5	58	61	55.5	52	60
VAR6	77.5	72.5	70	73.5	78	70

Table 5. Ranking of problem with five objectives, division of objectives and four species.

	PROBLEM	VARIANT	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
PROBLEMS WITH FIVE OBJECTIVES. DIVISION BY OBJECTIVES AND FOUR SPECIES	DTLZ1	MOEA/D	2	5	2	6	2	2
		VAR$_1$	5.5	5	5.5	2.5	5.5	5.5
		VAR$_2$	2	5	2	6	2	2
		VAR$_3$	5.5	2	5.5	2.5	5.5	5.5
		VAR$_4$	5.5	5	5.5	2.5	5.5	5.5
		VAR$_5$	5.5	1	5.5	2.5	5.5	5.5
		VAR$_6$	2	5	2	6	2	2
	DTLZ2	MOEA/D	6	6	6	6	6	6
		VAR$_1$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_2$	6	6	6	6	6	6
		VAR$_3$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_4$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_5$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_6$	6	6	6	6	6	6
	DTLZ3	MOEA/D	2	2	2	2	2	2
		VAR$_1$	6	5.5	5.5	5.5	6	5.5
		VAR$_2$	2	2	2	2	2	2
		VAR$_3$	6	5.5	5.5	5.5	6	5.5
		VAR$_4$	4	5.5	5.5	5.5	4	5.5
		VAR$_5$	6	5.5	5.5	5.5	6	5.5
		VAR$_6$	2	2	2	2	2	2
	DTLZ4	MOEA/D	5	6	6	6	5	5
		VAR$_1$	5	2.5	4	2.5	5	5
		VAR$_2$	5	6	6	6	5	5
		VAR$_3$	1.5	2.5	1	2.5	1.5	1
		VAR$_4$	5	2.5	3	2.5	5	5
		VAR$_5$	1.5	2.5	2	2.5	1.5	2
		VAR$_6$	5	6	6	6	5	5
	DTLZ5	MOEA/D	6	6	6	6	6	6
		VAR$_1$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_2$	6	6	6	6	6	6
		VAR$_3$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_4$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_5$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_6$	6	6	6	6	6	6
	DTLZ6	MOEA/D	2	2	2	2	2	2
		VAR$_1$	5.5	5.5	5.5	5.5	5.5	5.5
		VAR$_2$	2	2	2	2	2	2
		VAR$_3$	5.5	5.5	5.5	5.5	5.5	5.5
		VAR$_4$	5.5	5.5	5.5	5.5	5.5	5.5
		VAR$_5$	5.5	5.5	5.5	5.5	5.5	5.5
		VAR$_6$	2	2	2	2	2	2
	DTLZ7	MOEA/D	2	1	2	4	4	4
		VAR$_1$	5	5.5	5.5	4	4	4
		VAR$_2$	1	1	2	4	4	4
		VAR$_3$	5	5.5	5.5	4	4	4
		VAR$_4$	5	5.5	5.5	4	4	4
		VAR$_5$	5	5.5	5.5	4	4	4
		VAR$_6$	5	1	2	4	4	4
	WFG1	MOEA/D	2	2	3	5	2	3
		VAR$_1$	5	5.5	3	1.5	5.5	3
		VAR$_2$	5	2	3	5	2	3
		VAR$_3$	5	5.5	6.5	5	5.5	6.5
		VAR$_4$	5	5.5	3	1.5	5.5	3
		VAR5	5	5.5	6.5	5	5.5	6.5
		VAR6	1	2	3	5	2	3

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WFG2	MOEA/D	4	3	2	2.5	3	1
	VAR_1	4	3	5.5	5.5	3	5.5
	VAR_2	2	3	2	1	3	1
	VAR_3	6.5	6.5	5.5	5.5	6.5	5.5
	VAR_4	4	3	5.5	5.5	3	5.5
	VAR_5	6.5	6.5	5.5	5.5	6.5	5.5
	VAR_6	1	3	2	2.5	3	1
WFG3	MOEA/D	6	6	6	6	5	5
	VAR_1	3.5	2.5	3	2.5	5	5
	VAR_2	6	6	6	6	5	5
	VAR_3	1	2.5	1	2.5	1.5	1.5
	VAR_4	3.5	2.5	3	2.5	5	5
	VAR_5	2	2.5	3	2.5	1.5	1.5
	VAR_6	6	6	6	6	5	5
WFG4	MOEA/D	6	6	4	4	6	2
	VAR_1	2.5	2.5	4	4	2.5	5
	VAR_2	6	6	4	4	6	1
	VAR_3	2.5	2.5	4	4	2.5	5
	VAR_4	2.5	2.5	4	4	2.5	5
	VAR_5	2.5	2.5	4	4	2.5	5
	VAR_6	6	6	4	4	6	5
WFG5	MOEA/D	2	6	6	6	4	6
	VAR_1	5.5	2.5	2.5	2.5	4	2.5
	VAR_2	2	6	6	6	4	6
	VAR_3	5.5	2.5	2.5	2.5	4	2.5
	VAR_4	5.5	2.5	2.5	2.5	4	2.5
	VAR_5	5.5	2.5	2.5	2.5	4	2.5
	VAR_6	2	6	6	6	4	6
WFG6	MOEA/D	6	6	6	6	6	6
	VAR_1	2.5	2.5	2.5	2.5	2.5	2
	VAR_2	6	6	6	6	6	6
	VAR_3	2.5	2.5	2.5	2.5	2.5	4
	VAR_4	2.5	2.5	2.5	2.5	2.5	2
	VAR_5	2.5	2.5	2.5	2.5	2.5	2
	VAR_6	6	6	6	6	6	6
WFG7	MOEA/D	6	6	6	6	6	6
	VAR_1	2.5	2.5	2.5	2.5	2.5	2.5
	VAR_2	6	6	6	6	6	6
	VAR_3	2.5	2.5	2.5	2.5	2.5	2.5
	VAR_4	2.5	2.5	2.5	2.5	2.5	2.5
	VAR_5	2.5	2.5	2.5	2.5	2.5	2.5
	VAR_6	6	6	6	6	6	6
WFG8	MOEA/D	6	6	6	6	6	6
	VAR_1	2.5	2.5	2.5	2.5	2.5	3.5
	VAR_2	6	6	6	6	6	6
	VAR_3	2.5	2.5	2.5	2.5	2.5	3.5
	VAR_4	2.5	2.5	2.5	2.5	2.5	1.5
	VAR_5	2.5	2.5	2.5	2.5	2.5	1.5
	VAR_6	6	6	6	6	6	6
WFG9	MOEA/D	6	6	6	6	4.5	5.5
	VAR_1	2.5	2.5	2.5	2.5	1	2.5
	VAR_2	6	6	6	6	4.5	5.5
	VAR_3	2.5	2.5	2.5	2.5	4.5	5.5
	VAR_4	2.5	2.5	2.5	2.5	4.5	1
	VAR_5	2.5	2.5	2.5	2.5	4.5	2.5
	VAR_6	6	6	6	6	4.5	5.5

4.3 Experimental Conditions

Table 1 presents the experimental conditions used to validate the performance of coevolutionary algorithms with their different configurations and variants in solving standard problems.

The main objective was to identify the most effective or viable strategy that approximated the region of interest of the DM. The genetic operators employed were: random parent selection, SBX crossover, and polynomial-based mutation.

Table 6. Borda count of CO-MOEA/D with objective division and four species

MIN_EUCL				AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
75				71	79.5	69.5	67.5
55				59	51	59.5	62
75				71	78	69.5	66.5
55.5	57.5	54.5	59.5	63			
55	58	51	61	58.5			
54.5	60.5	54.5	59.5	57			
75	71	79.5	69.5	70.5			

Table 7. Ranking of problem with five objectives, division of objectives and two species

	PROBLEM	VARIANT	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
PROBLEMS WITH FIVE OBJECTIVES. DIVISION BY OBJECTIVES AND TWO SPECIES	DTLZ1	MOEA/D	6	6	5.5	6	6	6
		VAR$_1$	3.5	3.5	3	3.5	3.5	3.5
		VAR$_2$	6	1.5	5.5	1.5	6	6
		VAR$_3$	1	6	1	6	1.5	1.5
		VAR$_4$	3.5	3.5	5.5	3.5	3.5	3.5
		VAR$_5$	2	6	2	6	1.5	1.5
		VAR$_6$	6	1.5	5.5	1.5	6	6
	DTLZ2	MOEA/D	6	7	6	4.5	6	6
		VAR$_1$	2.5	3.5	2.5	4.5	4	2.5
		VAR$_2$	6	3.5	6	1	6	6
		VAR$_3$	2.5	3.5	2.5	4.5	2	2.5
		VAR$_4$	2.5	3.5	2.5	4.5	2	2.5
		VAR$_5$	2.5	3.5	2.5	4.5	2	2.5
		VAR$_6$	6	3.5	6	4.5	6	6
	DTLZ3	MOEA/D	5	4	5	4.5	5.5	5
		VAR$_1$	5	4	5	4.5	5.5	5
		VAR$_2$	5	4	5	4.5	5.5	5
		VAR$_3$	1.5	4	1.5	4.5	1	2
		VAR$_4$	5	4	5	4.5	1	5
		VAR$_5$	1.5	4	1.5	4.5	1	1
		VAR$_6$	5	4	5	1	5.5	5
	DTLZ4	MOEA/D	5	4	5	3	5	5.5
		VAR$_1$	5	4	5	3	5	1
		VAR$_2$	5	4	5	3	5	5.5
		VAR$_3$	1.5	4	1.5	6.5	1.5	1
		VAR$_4$	5	4	5	3	5	5.5
		VAR$_5$	1.5	4	1.5	6.5	1.5	1
		VAR$_6$	5	4	5	3	5	5.5
	DTLZ5	MOEA/D	7	1	7	1	5.5	7
		VAR$_1$	3.5	3	3.5	4.5	2	4
		VAR$_2$	3.5	5.5	3.5	4.5	2	4
		VAR$_3$	3.5	5.5	3.5	4.5	5.5	4
		VAR$_4$	3.5	5.5	3.5	4.5	5.5	4
		VAR$_5$	3.5	5.5	3.5	4.5	5.5	4
		VAR$_6$	3.5	2	3.5	4.5	2	1
	DTLZ6	MOEA/D	7	1	7	1	6.5	6.5
		VAR$_1$	4.5	2	4	2	4.5	4.5
		VAR$_2$	1	6	1	6	1	1
		VAR$_3$	4.5	6	4	6	4.5	4.5
		VAR$_4$	4.5	3.5	4	3.5	2.5	2.5
		VAR$_5$	4.5	6	4	6	6.5	6.5
		VAR$_6$	2	3.5	4	3.5	2.5	2.5
	DTLZ7	MOEA/D	6	5	6	1	6	5.5
		VAR$_1$	3.5	5	3	5.5	1	2
		VAR$_2$	6	2	6	1	6	5.5
		VAR$_3$	1.5	5	3	5.5	1	2
		VAR$_4$	1.5	5	1	5.5	1	2
		VAR$_5$	3.5	5	3	5.5	4	5.5
		VAR$_6$	6	1	6	1	6	5.5

WFG1	MOEA/D	4	4	7	6.5	4	7
	VAR_1	4	4	3.5	3	4	3.5
	VAR_2	4	4	3.5	6.5	4	3.5
	VAR_3	4	4	3.5	3	4	3.5
	VAR_4	4	4	3.5	3	4	3.5
	VAR_5	4	4	3.5	3	4	3.5
	VAR_6	4	4	3.5	3	4	3.5
WFG2	MOEA/D	6.5	4	1	1	7	4
	VAR_1	6.5	4	4.5	4.5	3.5	4
	VAR_2	3	4	4.5	4.5	3.5	4
	VAR_3	3	4	4.5	4.5	3.5	4
	VAR_4	3	4	4.5	4.5	3.5	4
	VAR_5	3	4	4.5	4.5	3.5	4
	VAR_6	3	4	4.5	4.5	3.5	4
WFG3	MOEA/D	4	4	1	1	4	1
	VAR_1	4	4	4.5	4.5	4	4.5
	VAR_2	4	4	4.5	4.5	4	4.5
	VAR_3	4	4	4.5	4.5	4	4.5
	VAR_4	4	4	4.5	4.5	4	4.5
	VAR_5	4	4	4.5	4.5	4	4.5
	VAR_6	4	4	4.5	4.5	4	4.5
WFG4	MOEA/D	6	7	6	1	7	6
	VAR_1	6	3.5	6	4.5	3.5	6
	VAR_2	2.5	3.5	1	4.5	3.5	1
	VAR_3	2.5	3.5	1	4.5	3.5	1
	VAR_4	2.5	3.5	1	4.5	3.5	4
	VAR_5	2.5	3.5	4	4.5	3.5	1
	VAR_6	6	3.5	6	4.5	3.5	6
WFG5	MOEA/D	6	7	6	1	6	6
	VAR_1	6	3.5	6	4.5	6	6
	VAR_2	2.5	3.5	1	4.5	2.5	2.5
	VAR_3	2.5	3.5	3.5	4.5	2.5	2.5
	VAR_4	2.5	3.5	2	4.5	2.5	2.5
	VAR_5	2.5	3.5	3.5	4.5	2.5	2.5
	VAR_6	6	3.5	6	4.5	6	6
WFG6	MOEA/D	6.5	6.5	5	4	7	4.5
	VAR_1	4	4	1.5	4	4.5	4.5
	VAR_2	4	4	5	4	4.5	4.5
	VAR_3	1	1.5	5	4	1.5	4.5
	VAR_4	4	4	1.5	4	4.5	1
	VAR_5	2	1.5	5	4	1.5	4.5
	VAR_6	6.5	6.5	5	4	4.5	4.5
WFG7	MOEA/D	2	2	2.5	1	6	3
	VAR_1	2	2	2.5	1	2.5	3
	VAR_2	5.5	5.5	5.5	5.5	6	3
	VAR_3	5.5	5.5	5.5	5.5	2.5	6
	VAR_4	5.5	5.5	5.5	5.5	6	6
	VAR_5	5.5	5.5	5.5	5.5	2.5	6
	VAR_6	2	2	1	1	2.5	1
WFG8	MOEA/D	4	1	4	1	6	7
	VAR_1	4	4.5	4	4.5	1.5	3.5
	VAR_2	4	4.5	4	4.5	6	3.5
	VAR_3	4	4.5	4	4.5	1.5	3.5
	VAR_4	4	4.5	4	4.5	3.5	3.5
	VAR_5	4	4.5	4	4.5	3.5	3.5
	VAR_6	4	4.5	4	4.5	6	3.5
WFG9	MOEA/D	6	6.5	4	1.5	6.5	4
	VAR_1	6	6.5	4	5	6.5	4
	VAR_2	2	3.5	4	5	2	4
	VAR_3	2	1	4	5	2	4
	VAR_4	4	3.5	4	5	4.5	4
	VAR_5	2	3.5	4	5	2	4
	VAR_6	6	3.5	4	1.5	4.5	4

5 Experimentation and Results

In this study, a comparative analysis of various configurations of the cooperative coevolutionary algorithm was conducted to solve problems from both the WFG1-9 and DTLZ1-7 families.

Different scenarios were explored, considering the presence of five and ten objectives, as well as the application of division strategies by objectives and variables.

Additionally, divisions involving 2, 4, and 8 species were evaluated, using the solving algorithm MOEA/D with its variants: VAR_1, VAR_2, VAR_3, VAR_4, VAR_5, and VAR_6 [14].

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Table 8. Borda count of CO-MOEA/D with variables division and two species

VARIANTE	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
MOEA/D	87	70	78	39	94	84
VAR1	70	61	62.5	63	61.5	61.5
VAR2	64	63	65	65	67.5	63.5
VAR3	44.5	65.5	52.5	77.5	42	51
VAR4	59	65.5	57	69	56.5	58
VAR5	48.5	68	56.5	77.5	49	55.5
VAR6	75	55	73.5	51	71.5	68.5

Table 9. Ranking of problem with five objectives, division of variables and four specie

	PROBLEM	VARIANT	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
PROBLEMS WITH FIVE OBJECTIVES. DIVISION BY VARIABLES AND FOUR SPECIES	**DTLZ1**	MOEA/D	6	6	6	5.5	6	6
		VAR$_1$	4	2.5	4	2	2.5	2.5
		VAR$_2$	6	2.5	6	2	6	6
		VAR$_3$	2	6	2	5.5	2.5	2.5
		VAR$_4$	2	2.5	2	5.5	2.5	2.5
		VAR$_5$	2	6	2	5.5	2.5	2.5
		VAR$_6$	6	2.5	6	2	6	6
	DTLZ2	MOEA/D	6	7	6	4	6	6
		VAR$_1$	2.5	3.5	2.5	4	2.5	2.5
		VAR$_2$	6	3.5	6	4	6	6
		VAR$_3$	2.5	3.5	2.5	4	2.5	2.5
		VAR$_4$	2.5	3.5	2.5	4	2.5	2.5
		VAR$_5$	2.5	3.5	2.5	4	2.5	2.5
		VAR$_6$	6	3.5	6	4	6	6
	DTLZ3	MOEA/D	6	4.5	6	3	6	6
		VAR$_1$	2.5	4.5	2.5	6	4	2.5
		VAR$_2$	6	4.5	6	3	6	6
		VAR$_3$	2.5	4.5	2.5	6	2	2.5
		VAR$_4$	2.5	4.5	2.5	3	2	2.5
		VAR$_5$	2.5	4.5	2.5	6	2	2.5
		VAR$_6$	6	1	6	1	6	6
	DTLZ4	MOEA/D	5	5	6.5	3	5	5.5
		VAR$_1$	5	2	3	3	5	1
		VAR$_2$	5	5	6.5	3	5	5.5
		VAR$_3$	1.5	5	3	6.5	1.5	1
		VAR$_4$	5	1	3	3	5	5.5
		VAR$_5$	1.5	5	3	6.5	1.5	1
		VAR$_6$	5	5	3	3	5	5.5
	DTLZ5	MOEA/D	7	1	7	1	5.5	6
		VAR$_1$	3.5	2.5	3.5	2	2	2.5
		VAR$_2$	3.5	5.5	3.5	5	2	2.5
		VAR$_3$	3.5	5.5	3.5	5	5.5	6
		VAR$_4$	3.5	5.5	3.5	5	5.5	2.5
		VAR$_5$	3.5	5.5	3.5	5	5.5	6
		VAR$_6$	3.5	2.5	3.5	5	2	2.5
	DTLZ6	MOEA/D	7	5.5	7	6	6	6
		VAR$_1$	4	1	4	1.5	3.5	3.5
		VAR$_2$	1	5.5	1	3.5	1	1
		VAR$_3$	4	5.5	4	6	6	6
		VAR$_4$	4	1	4	1.5	3.5	3.5
		VAR$_5$	4	5.5	4	6	6	6
		VAR$_6$	4	1	4	3.5	2	2
	DTLZ7	MOEA/D	4.5	5	4	5	4.5	5
		VAR$_1$	4.5	5	4	5	4.5	5
		VAR$_2$	4.5	1	4	1.5	4.5	1.5
		VAR$_3$	4.5	5	4	5	4.5	5
		VAR$_4$	1	5	4	5	1	1.5
		VAR$_5$	4.5	5	4	5	4.5	5
		VAR$_6$	4.5	2	4	1.5	4.5	5

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WFG1	MOEA/D	4	4	7	6.5	4	7
	VAR$_1$	4	4	1	1	4	3.5
	VAR$_2$	4	4	4	6.5	4	3.5
	VAR$_3$	4	4	4	3.5	4	3.5
	VAR$_4$	4	4	4	3.5	4	3.5
	VAR$_5$	4	4	4	3.5	4	3.5
	VAR$_6$	4	4	4	3.5	4	3.5
WFG2	MOEA/D	6.5	5	1.5	1	6.5	4.5
	VAR$_1$	6.5	5	1.5	4.5	6.5	1
	VAR$_2$	3	5	5	4.5	3	4.5
	VAR$_3$	3	5	5	4.5	3	4.5
	VAR$_4$	3	1.5	5	4.5	3	4.5
	VAR$_5$	3	1.5	5	4.5	3	4.5
	VAR$_6$	3	5	5	4.5	3	4.5
WFG3	MOEA/D	4	4	4	1	4	1
	VAR$_1$	4	4	4	4.5	4	4.5
	VAR$_2$	4	4	4	4.5	4	4.5
	VAR$_3$	4	4	4	4.5	4	4.5
	VAR$_4$	4	4	4	4.5	4	4.5
	VAR$_5$	4	4	4	4.5	4	4.5
	VAR$_6$	4	4	4	4.5	4	4.5
WFG4	MOEA/D	7	7	6	1	7	7
	VAR$_1$	4	3.5	2.5	4.5	4.5	3.5
	VAR$_2$	1	3.5	2.5	4.5	1	3.5
	VAR$_3$	4	3.5	6	4.5	4.5	3.5
	VAR$_4$	4	3.5	2.5	4.5	4.5	3.5
	VAR$_5$	4	3.5	2.5	4.5	2	3.5
	VAR$_6$	4	3.5	6	4.5	4.5	3.5
WFG5	MOEA/D	7	7	1	1	6.5	6
	VAR$_1$	5	3.5	5.5	4.5	6.5	6
	VAR$_2$	2	3.5	1	4.5	4	1.5
	VAR$_3$	2	3.5	5.5	4.5	1.5	3.5
	VAR$_4$	5	3.5	1	4.5	4	3.5
	VAR$_5$	2	3.5	5.5	4.5	1.5	1.5
	VAR$_6$	5	3.5	5.5	4.5	4	6
WFG6	MOEA/D	6.5	6.5	5	1	6.5	4
	VAR$_1$	2.5	3	5	4.5	4.5	4
	VAR$_2$	5	6.5	1.5	4.5	4.5	4
	VAR$_3$	2.5	3	5	4.5	2	4
	VAR$_4$	2.5	3	1.5	4.5	2	4
	VAR$_5$	2.5	3	5	4.5	2	4
	VAR$_6$	6.5	3	5	4.5	6.5	4
WFG7	MOEA/D	2	4	5	1	1	4
	VAR$_1$	2	4	1	4.5	1	4
	VAR$_2$	5.5	4	5	4.5	5.5	4
	VAR$_3$	5.5	4	5	4.5	5.5	4
	VAR$_4$	5.5	4	5	4.5	5.5	4
	VAR$_5$	5.5	4	5	4.5	5.5	4
	VAR$_6$	2	4	2	4.5	1	4
WFG8	MOEA/D	4.5	1	4.5	1	5.5	7
	VAR$_1$	4.5	4.5	4.5	4.5	5.5	3.5
	VAR$_2$	4.5	4.5	4.5	4.5	5.5	3.5
	VAR$_3$	4.5	4.5	4.5	4.5	2.5	3.5
	VAR$_4$	4.5	4.5	4.5	4.5	2.5	3.5
	VAR$_5$	1	4.5	1	4.5	1	3.5
	VAR$_6$	4.5	4.5	4.5	4.5	5.5	3.5
WFG9	MOEA/D	6.5	7	4	1	6.5	4
	VAR$_1$	6.5	3.5	4	4.5	6.5	4
	VAR$_2$	2	3.5	4	4.5	1	4
	VAR$_3$	2	3.5	4	4.5	1	4
	VAR$_4$	4.5	3.5	4	4.5	4.5	4
	VAR$_5$	2	3.5	4	4.5	1	4
	VAR$_6$	4.5	3.5	4	4.5	4.5	4

The statistical comparison for each problem was applied using the Quality indicators Avg-Eucl, Avg-Tcheb, Med-Eucl, Med-Tcheb, Min-Eucl, and Min-Tcheb.

The experimental setups included a limit of 100,000 evaluations, a population of 100 individuals, and a neighborhood size T=10.

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Table 10. Borda count of CO-MOEA/D with variables division and four species

VARIANTE	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
MOEA/D	89.5	79.5	80.5	42	86.5	85
VAR1	65	56	52.5	60.5	67	53.5
VAR2	63	66	64.5	64.5	63	61.5
VAR3	52	70	64.5	77.5	52.5	60.5
VAR4	57.5	54.5	53	66.5	56	55.5
VAR5	48.5	66.5	57.5	77.5	48.5	58.5
VAR6	72.5	52.5	72.5	59.5	68.5	70.5

Table 11. Ranking of problem with five objectives, division of variables and eight species

	PROBLEM	VARIANT	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
PROBLEMS WITH FIVE OBJECTIVES. DIVISION BY VARIABLES AND EIGHT SPECIES	**DTLZ1**	MOEA/D	6	5.5	6	5.5	6	6
		VAR_1	2.5	1	2.5	1	2.5	2.5
		VAR_2	6	1	6	1	6	6
		VAR_3	2.5	5.5	2.5	5.5	2.5	2.5
		VAR_4	2.5	5.5	2.5	5.5	2.5	2.5
		VAR_5	2.5	5.5	2.5	5.5	2.5	2.5
		VAR_6	6	1	6	1	6	6
	DTLZ2	MOEA/D	6	6.5	6	4	6	6
		VAR_1	2.5	6.5	2.5	4	4	2.5
		VAR_2	6	3	6	4	6	6
		VAR_3	2.5	3	2.5	4	2	2.5
		VAR_4	2.5	3	2.5	4	2	2.5
		VAR_5	2.5	3	2.5	4	2	2.5
		VAR_6	6	3	6	4	6	6
	DTLZ3	MOEA/D	6	1.5	6	1.5	6	6
		VAR_1	4	5	4	5	3	3
		VAR_2	6	1.5	6	1.5	6	6
		VAR_3	2	5	2	5	3	3
		VAR_4	2	5	2	5	1	1
		VAR_5	2	5	2	5	3	3
		VAR_6	6	5	6	5	6	6
	DTLZ4	MOEA/D	5	3	4.5	3	5.5	4
		VAR_1	5	3	4.5	3	5.5	4
		VAR_2	5	3	4.5	3	5.5	4
		VAR_3	1.5	6.5	4.5	6.5	1	4
		VAR_4	5	3	1	3	5.5	4
		VAR_5	1.5	6.5	4.5	6.5	1	4
		VAR_6	5	3	4.5	3	1	4
	DTLZ5	MOEA/D	4.5	1	6.5	1	4.5	5.5
		VAR_1	1	2	1	4.5	4.5	2.5
		VAR_2	4.5	5	3.5	4.5	4.5	1
		VAR_3	4.5	5	3.5	4.5	4.5	5.5
		VAR_4	4.5	5	3.5	4.5	4.5	5.5
		VAR_5	4.5	5	3.5	4.5	4.5	5.5
		VAR_6	4.5	5	6.5	4.5	1	2.5
	DTLZ6	MOEA/D	5.5	6	5.5	6	5	5
		VAR_1	5.5	2	5.5	2	5	5
		VAR_2	1	2	1	2	1.5	1
		VAR_3	5.5	6	5.5	6	5	5
		VAR_4	1	4	1	4	5	5
		VAR_5	5.5	6	5.5	6	5	5
		VAR_6	1	2	1	2	1.5	2
	DTLZ7	MOEA/D	4	2.5	4.5	1	4	4.5
		VAR_1	4	5.5	4.5	5.5	4	4.5
		VAR_2	4	1	1	1	4	1
		VAR_3	4	5.5	4.5	5.5	4	4.5
		VAR_4	4	5.5	4.5	5.5	4	4.5
		VAR_5	4	5.5	4.5	5.5	4	4.5
		VAR_6	4	2.5	4.5	1	4	4.5

WFG1	MOEA/D	4	4	7	7	4	7
	VAR_1	4	4	3.5	3.5	4	3.5
	VAR_2	4	4	3.5	3.5	4	3.5
	VAR_3	4	4	3.5	3.5	4	3.5
	VAR_4	4	4	3.5	3.5	4	3.5
	VAR_5	4	4	3.5	3.5	4	3.5
	VAR_6	4	4	3.5	3.5	4	3.5
WFG2	MOEA/D	5.5	4	4	1	4.5	4
	VAR_1	5.5	4	4	4.5	4.5	4
	VAR_2	5.5	4	4	4.5	4.5	4
	VAR_3	2	4	4	4.5	4.5	4
	VAR_4	2	4	4	4.5	1	4
	VAR_5	2	4	4	4.5	4.5	4
	VAR_6	5.5	4	4	4.5	4.5	4
WFG3	MOEA/D	5	4	1	1	4	1
	VAR_1	5	4	4.5	4.5	4	4.5
	VAR_2	5	4	4.5	4.5	4	4.5
	VAR_3	1.5	4	4.5	4.5	4	4.5
	VAR_4	1.5	4	4.5	4.5	4	4.5
	VAR_5	5	4	4.5	4.5	4	4.5
	VAR_6	5	4	4.5	4.5	4	4.5
WFG4	MOEA/D	7	7	4	1	6.5	4.5
	VAR_1	4.5	3.5	4	4.5	6.5	4.5
	VAR_2	1.5	3.5	4	4.5	2	4.5
	VAR_3	1.5	3.5	4	4.5	2	4.5
	VAR_4	4.5	3.5	4	4.5	4.5	4.5
	VAR_5	4.5	3.5	4	4.5	2	4.5
	VAR_6	4.5	3.5	4	4.5	4.5	1
WFG5	MOEA/D	7	7	4	1	7	5.5
	VAR_1	4	3.5	4	4.5	3.5	5.5
	VAR_2	1	3.5	4	4.5	3.5	1
	VAR_3	4	3.5	4	4.5	3.5	2.5
	VAR_4	4	3.5	4	4.5	3.5	2.5
	VAR_5	4	3.5	4	4.5	3.5	5.5
	VAR_6	4	3.5	4	4.5	3.5	5.5
WFG6	MOEA/D	7	6	4	4	7	4
	VAR_1	3.5	2.5	4	4	3.5	4
	VAR_2	3.5	2.5	4	4	3.5	4
	VAR_3	3.5	2.5	4	4	3.5	4
	VAR_4	3.5	6	4	4	3.5	4
	VAR_5	3.5	2.5	4	4	3.5	4
	VAR_6	3.5	6	4	4	3.5	4
WFG7	MOEA/D	2	1	4	1	1	4
	VAR_1	2	4.5	4	5	4.5	4
	VAR_2	5.5	4.5	4	5	4.5	4
	VAR_3	5.5	4.5	4	5	4.5	4
	VAR_4	5.5	4.5	4	5	4.5	4
	VAR_5	5.5	4.5	4	5	4.5	4
	VAR_6	2	4.5	4	2	4.5	4
WFG8	MOEA/D	4	1	4	1	4	4
	VAR_1	4	4.5	4	4.5	4	4
	VAR_2	4	4.5	4	4.5	4	4
	VAR_3	4	4.5	4	4.5	4	4
	VAR_4	4	4.5	4	4.5	4	4
	VAR_5	4	4.5	4	4.5	4	4
	VAR_6	4	4.5	4	4.5	4	4
WFG9	MOEA/D	6.5	6.5	4	4	7	4
	VAR_1	4.5	3	4	4	5	4
	VAR_2	1	3	4	4	1	4
	VAR_3	2.5	3	4	4	1	4
	VAR_4	4.5	3	4	4	5	4
	VAR_5	2.5	3	4	4	1	4
	VAR_6	6.5	6.5	4	4	5	4

The polynomial mutation probability was set to 0.14, while the SBX crossover probability was kept at 1.0.

Two division strategies were evaluated: one based on objectives (with 5 and 10 objectives) and another by variables (with 9 and 100 variables), considering the division of species (2, 4, and 8).

The Borda Count method was applied to evaluate the results of thirty-five coevolutionaries (see Table 1).

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Table 12. Borda count of CO-MOEA/D with variables division and eight species

VARIANTE	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
MOEA/D	85	66.5	75	43	82	75
VAR1	61.5	58.5	60.5	64	68	62
VAR2	63.5	50	64	56	64.5	58.5
VAR3	51	70	61	76	53	62
VAR4	55	68	53	70.5	58.5	60
VAR5	57.5	70	61	76	53	65
VAR6	71.5	62	70.5	56.5	63	65.5

Table 13. Borda count of CO-MOEA/D with objective division and two species

	PROBLEM	VARIANT	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
PROBLEMS WITH TEN OBJECTIVES. DIVISION BY OBJECTIVES AND TWO SPECIES	**DTLZ1**	MOEA/D	3.5	6	3.5	5.5	4.5	4.5
		VAR$_1$	3.5	2.5	3.5	2	1	1
		VAR$_2$	3.5	6	3.5	5.5	6.5	6.5
		VAR$_3$	3.5	2.5	3.5	2	1	1
		VAR$_4$	3.5	2.5	3.5	2	1	1
		VAR$_5$	7	6	7	5.5	6.5	6.5
		VAR$_6$	3.5	2.5	3.5	5.5	4.5	4.5
	DTLZ2	MOEA/D	6	6	6	6	6	6
		VAR$_1$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_2$	6	6	6	6	6	6
		VAR$_3$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_4$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_5$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_6$	6	6	6	6	6	6
	DTLZ3	MOEA/D	1	6	1	6	4	4
		VAR$_1$	4.5	3.5	4.5	2.5	4	4
		VAR$_2$	4.5	6	4.5	6	4	4
		VAR$_3$	4.5	3.5	4.5	2.5	4	4
		VAR$_4$	4.5	1.5	4.5	2.5	4	4
		VAR$_5$	4.5	1.5	4.5	2.5	4	4
		VAR$_6$	4.5	6	4.5	6	4	4
	DTLZ4	MOEA/D	6	6	6	6	6	6
		VAR$_1$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_2$	6	6	6	6	6	6
		VAR$_3$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_4$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_5$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_6$	6	6	6	6	6	6
	DTLZ5	MOEA/D	6	6	6	2	6	6
		VAR$_1$	2.5	2.5	2.5	5.5	2.5	2.5
		VAR$_2$	6	6	6	2	6	6
		VAR$_3$	2.5	2.5	2.5	5.5	2.5	2.5
		VAR$_4$	2.5	2.5	2.5	5.5	2.5	2.5
		VAR$_5$	2.5	2.5	2.5	5.5	2.5	2.5
		VAR$_6$	6	6	6	2	6	6
	DTLZ6	MOEA/D	5	5	5	1	5	5
		VAR$_1$	5	5	5	4.5	5	5
		VAR$_2$	1.5	5	1.5	4.5	1.5	1.5
		VAR$_3$	5	1.5	5	4.5	5	5
		VAR$_4$	5	1.5	5	4.5	5	5
		VAR$_5$	5	5	5	4.5	5	5
		VAR$_6$	1.5	5	1.5	4.5	1.5	1.5
	DTLZ7	MOEA/D	6	6	6	6	5.5	6
		VAR$_1$	2.5	2.5	2.5	2.5	2	2
		VAR$_2$	6	6	6	6	5.5	6
		VAR$_3$	2.5	2.5	2.5	2.5	5.5	4
		VAR$_4$	2.5	2.5	2.5	2.5	2	2
		VAR$_5$	2.5	2.5	2.5	2.5	2	2
		VAR$_6$	6	6	6	6	5.5	6

WFG1	MOEA/D	3	3	3	2	2	2.5
	VAR_1	3	3	3	5.5	5.5	5.5
	VAR_2	3	3	3	2	2	2.5
	VAR_3	6.5	6.5	6.5	5.5	5.5	5.5
	VAR_4	3	3	3	5.5	5.5	5.5
	VAR_5	6.5	6.5	6.5	5.5	5.5	5.5
	VAR_6	3	3	3	2	2	1
WFG2	MOEA/D	5	5	1	4	3	4
	VAR_1	5	5	5.5	4	5.5	4
	VAR_2	1	1.5	5.5	4	1	4
	VAR_3	5	5	1	4	5.5	4
	VAR_4	5	5	5.5	4	5.5	4
	VAR_5	5	5	1	4	5.5	4
	VAR_6	2	1.5	5.5	4	2	4
WFG3	MOEA/D	4	4	6	4	1	6
	VAR_1	4	4	2.5	4	5.5	2.5
	VAR_2	4	4	6	4	2.5	6
	VAR_3	4	4	2.5	4	5.5	2.5
	VAR_4	4	4	2.5	4	5.5	2.5
	VAR_5	4	4	2.5	4	5.5	2.5
	VAR_6	4	4	6	4	2.5	6
WFG4	MOEA/D	6	6	6	4	4	6
	VAR_1	2.5	1.5	3.5	4	4	2.5
	VAR_2	2.5	6	6	4	4	6
	VAR_3	6	3.5	1.5	4	4	2.5
	VAR_4	2.5	1.5	3.5	4	4	2.5
	VAR_5	6	3.5	1.5	4	4	2.5
	VAR_6	2.5	6	6	4	4	6
WFG5	MOEA/D	1	1	4.5	7	3	4.5
	VAR_1	4.5	5.5	4.5	3.5	3	1
	VAR_2	3	2.5	4.5	3.5	3	4.5
	VAR_3	6.5	5.5	4.5	3.5	6.5	4.5
	VAR_4	4.5	5.5	4.5	3.5	3	2
	VAR_5	6.5	5.5	1	3.5	6.5	7
	VAR_6	2	2.5	4.5	3.5	3	4.5
WFG6	MOEA/D	5	5	5	4	5.5	5.5
	VAR_1	1.5	1	5	4	1	2.5
	VAR_2	5	5	5	4	5.5	5.5
	VAR_3	5	5	1.5	4	5.5	1
	VAR_4	1.5	2	5	4	1	5.5
	VAR_5	5	5	1.5	4	1	2.5
	VAR_6	5	5	5	4	5.5	5.5
WFG7	MOEA/D	5	5	6	6	5	6
	VAR_1	2	1.5	2.5	2.5	1.5	3.5
	VAR_2	5	5	6	6	5	6
	VAR_3	5	5	2.5	2.5	5	1.5
	VAR_4	1	1.5	2.5	2.5	1.5	3.5
	VAR_5	5	5	2.5	2.5	5	1.5
	VAR_6	5	5	6	6	5	6
WFG8	MOEA/D	5	7	4.5	5	5.5	2.5
	VAR_1	5	3.5	4.5	5	5.5	5.5
	VAR_2	5	3.5	4.5	5	2.5	1
	VAR_3	2	3.5	4.5	1.5	2.5	5.5
	VAR_4	5	3.5	4.5	5	5.5	5.5
	VAR_5	1	3.5	1	1.5	1	5.5
	VAR_6	5	3.5	4.5	5	5.5	2.5
WFG9	MOEA/D	2	4	5.5	4.5	2	6
	VAR_1	5.5	4	2	4.5	5.5	2
	VAR_2	2	4	5.5	4.5	2	6
	VAR_3	5.5	4	2	4.5	5.5	2
	VAR_4	5.5	4	5.5	4.5	5.5	4
	VAR_5	5.5	4	2	1	5.5	2
	VAR_6	2	4	5.5	4.5	2	6

For each problem, a classification of the seven variants was carried out with five and ten objectives ordered from lowest to highest (see Table 3 a la 22). To calculate the Borda count, the results of each indicator for each problem were added.

Table 14. Ranking of problem with ten objectives, division of objectives and two species

VARIANTE	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
MOEA/D	69.5	81	75	73	68	80.5
VAR1	56	50	56	59	56.5	48.5
VAR2	64	75.5	79.5	73	63	77.5
VAR3	68.5	59.5	49.5	55.5	68.5	50.5
VAR4	55	45.5	59.5	59	56.5	54.5
VAR5	71	64.5	46	55.5	64.5	58
VAR6	64	72	79.5	73	65	75.5

Table 15. Borda count of CO-MOEA/D with objective division and four species

	PROBLEM	VARIANT	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
PROBLEMS WITH TEN OBJECTIVES. DIVISION BY OBJECTIVES AND FOUR SPECIES	**DTLZ1**	MOEA/D	2	4	2	4	1	1
		VAR$_1$	5.5	4	5.5	4	5.5	5.5
		VAR$_2$	2	4	2	4	1	1
		VAR$_3$	5.5	4	5.5	4	5.5	5.5
		VAR$_4$	5.5	4	5.5	4	5.5	5.5
		VAR$_5$	5.5	4	5.5	4	5.5	5.5
		VAR$_6$	2	4	2	4	1	1
	DTLZ2	MOEA/D	4	5	5	6	4	4.5
		VAR$_1$	4	5	1.5	4	4	4.5
		VAR$_2$	4	5	5	6	4	4.5
		VAR$_3$	4	2	5	1	4	4.5
		VAR$_4$	4	5	1.5	1	4	1
		VAR$_5$	4	1	5	1	4	4.5
		VAR$_6$	4	5	5	6	4	4.5
	DTLZ3	MOEA/D	2	2	2	2	2	2
		VAR$_1$	5.5	5.5	5.5	5.5	5.5	5.5
		VAR$_2$	2	2	2	2	2	2
		VAR$_3$	5.5	5.5	5.5	5.5	5.5	5.5
		VAR$_4$	5.5	5.5	5.5	5.5	5.5	5.5
		VAR$_5$	5.5	5.5	5.5	5.5	5.5	5.5
		VAR$_6$	2	2	2	2	2	2
	DTLZ4	MOEA/D	6	6	6	6	6	6
		VAR$_1$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_2$	6	6	6	6	6	6
		VAR$_3$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_4$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_5$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_6$	6	6	6	6	6	6
	DTLZ5	MOEA/D	6	6	6	1	6	6
		VAR$_1$	2.5	2.5	2.5	4.5	1.5	2.5
		VAR$_2$	6	6	6	4.5	6	6
		VAR$_3$	2.5	2.5	2.5	4.5	3.5	2.5
		VAR$_4$	2.5	2.5	2.5	4.5	1.5	2.5
		VAR$_5$	2.5	2.5	2.5	4.5	3.5	2.5
		VAR$_6$	6	6	6	4.5	6	6
	DTLZ6	MOEA/D	4	1	4	1	4	4
		VAR$_1$	4	4.5	4	4.5	4	4
		VAR$_2$	4	4.5	4	4.5	4	4
		VAR$_3$	4	4.5	4	4.5	4	4
		VAR$_4$	4	4.5	4	4.5	4	4
		VAR$_5$	4	4.5	4	4.5	4	4
		VAR$_6$	4	4.5	4	4.5	4	4
	DTLZ7	MOEA/D	6	6	6	6	6	6
		VAR$_1$	4	4	3.5	2.5	3	3.5
		VAR$_2$	6	6	6	6	6	6
		VAR$_3$	2	1	2	2.5	3	1.5
		VAR$_4$	2	1	3.5	2.5	3	3.5
		VAR$_5$	2	1	1	2.5	1	1.5
		VAR$_6$	6	6	6	6	6	6

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WFG1	MOEA/D	2	1	2	1	1	3
	VAR_1	4	4	4	4.5	3.5	3
	VAR_2	2	2	2	1	3.5	3
	VAR_3	6.5	6.5	6	6.5	6.5	6.5
	VAR_4	5	4	6	4.5	3.5	3
	VAR_5	6.5	6.5	6	6.5	6.5	6.5
	VAR_6	2	4	2	1	3.5	3
WFG2	MOEA/D	2	1	1	2	3	4
	VAR_1	6	4	5.5	5.5	3	4
	VAR_2	2	4	1	2	3	4
	VAR_3	6	6.5	5.5	5.5	6.5	4
	VAR_4	4	4	5.5	5.5	3	4
	VAR_5	6	6.5	5.5	5.5	6.5	4
	VAR_6	2	2	1	2	3	4
WFG3	MOEA/D	2	2	6	5	2	6
	VAR_1	5.5	5.5	2.5	1.5	5.5	2.5
	VAR_2	2	2	6	5	2	6
	VAR_3	5.5	5.5	2.5	5	5.5	2.5
	VAR_4	5.5	5.5	2.5	1.5	5.5	2.5
	VAR_5	5.5	5.5	2.5	5	5.5	2.5
	VAR_6	2	2	6	5	2	6
WFG4	MOEA/D	3	2	6	4	1	6
	VAR_1	5.5	5.5	2	4	5.5	2
	VAR_2	1	2	6	4	1	6
	VAR_3	5.5	5.5	2	4	5.5	2
	VAR_4	5.5	5.5	4	4	5.5	4
	VAR_5	5.5	5.5	2	4	5.5	2
	VAR_6	2	2	6	4	1	6
WFG5	MOEA/D	2	1	5.5	5	1	6
	VAR_1	5.5	5.5	5.5	5	5.5	3.5
	VAR_2	2	1	5.5	5	2	6
	VAR_3	5.5	5.5	2	1.5	5.5	2
	VAR_4	5.5	5.5	3	5	5.5	3.5
	VAR_5	5.5	5.5	1	1.5	5.5	1
	VAR_6	2	1	5.5	5	3	6
WFG6	MOEA/D	5	5	6	6	5	6
	VAR_1	1	1	4	2	1.5	6
	VAR_2	5	5	6	6	5	6
	VAR_3	5	5	2	2	5	1.5
	VAR_4	2	2	2	4	1.5	3.5
	VAR_5	5	5	2	2	5	1.5
	VAR_6	5	5	6	6	5	3.5
WFG7	MOEA/D	2	6	6	6	2	6
	VAR_1	5.5	2.5	2.5	2.5	5.5	2.5
	VAR_2	2	6	6	6	2	6
	VAR_3	5.5	2.5	2.5	2.5	5.5	2.5
	VAR_4	5.5	2.5	2.5	2.5	5.5	2.5
	VAR_5	5.5	2.5	2.5	2.5	5.5	2.5
	VAR_6	2	6	6	6	2	6
WFG8	MOEA/D	6	6	6	6	6	6
	VAR_1	2.5	2.5	2.5	2.5	2.5	2.5
	VAR_2	6	6	6	6	6	6
	VAR_3	2.5	2.5	2.5	2.5	2.5	2.5
	VAR_4	2.5	2.5	2.5	2.5	2.5	2.5
	VAR_5	2.5	2.5	2.5	2.5	2.5	2.5
	VAR_6	6	6	6	6	6	6
WFG9	MOEA/D	2	2	6	6	1	7
	VAR_1	5.5	5.5	2.5	2.5	4.5	4
	VAR_2	2	2	6	6	4.5	4
	VAR_3	5.5	5.5	2.5	2.5	4.5	4
	VAR_4	5.5	5.5	2.5	2.5	4.5	4
	VAR_5	5.5	5.5	2.5	2.5	4.5	1
	VAR_6	2	2	6	6	4.5	4

For example, in Table 3, the AVG-EUCL results of the MOEA/D variant of the DTLZ1 problem were added with the AVG-EUCL results of the VAR1 variant, for each problem (DTLZ1- WFG9).

This allows for the weighted sums, shown in Table 4. Given that these are minimization problems, the configurations showing the lowest values for each indicator were chosen (highlighted in bold). The purpose of this selection was to determine which of the best configurations stood out as the most outstanding.

This indicates the best parameter configuration for the cooperative coevolutionary algorithm.

Table 16. Ranking of problem with ten objectives, division of objectives and four species

VARIANTE	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
MOEA/D	56	56	75.5	67	51	79.5
VAR1	69	64	56	57.5	63	58
VAR2	54	63.5	75.5	74	58	76.5
VAR3	73.5	67	54.5	56.5	75	53.5
VAR4	67	62	55.5	56.5	63	54
VAR5	73.5	66	52.5	56.5	73	49.5
VAR6	55	63.5	75.5	74	59	74

Table 17. Borda count of CO-MOEA/D with division by variables and two species

	PROBLEM	VARIANT	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
PROBLEMS WITH TEN OBJECTIVES. DIVISION BY VARIABLES AND TWO SPECIES	DTLZ1	MOEA/D	6	5	6	4.5	6	6
		VAR$_1$	2.5	2	2.5	4.5	2.5	2.5
		VAR$_2$	6	1	6	1	6	6
		VAR$_3$	2.5	5	2.5	4.5	2.5	2.5
		VAR$_4$	2.5	5	2.5	4.5	2.5	2.5
		VAR$_5$	2.5	5	2.5	4.5	2.5	2.5
		VAR$_6$	6	5	6	4.5	6	6
	DTLZ2	MOEA/D	6	6	6	6.5	6	6
		VAR$_1$	2.5	3.5	2.5	1.5	2.5	2.5
		VAR$_2$	6	6	6	4	6	6
		VAR$_3$	2.5	3.5	2.5	4	2.5	2.5
		VAR$_4$	4	1.5	4	1.5	2.5	2.5
		VAR$_5$	1	1.5	1	4	2.5	2.5
		VAR$_6$	6	6	6	6.5	6	6
	DTLZ3	MOEA/D	4.5	6	4.5	5	4	4
		VAR$_1$	4.5	2.5	4.5	5	4	4
		VAR$_2$	1	2.5	1	1.5	4	4
		VAR$_3$	4.5	6	4.5	5	4	4
		VAR$_4$	4.5	2.5	4.5	5	4	4
		VAR$_5$	4.5	6	4.5	5	4	4
		VAR$_6$	4.5	2.5	4.5	1.5	4	4
	DTLZ4	MOEA/D	6	6	6	6	6	6
		VAR$_1$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_2$	6	6	6	6	6	6
		VAR$_3$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_4$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_5$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_6$	6	6	6	6	6	6
	DTLZ5	MOEA/D	7	7	7	1	7	7
		VAR$_1$	4.5	3.5	3.5	4.5	3.5	3.5
		VAR$_2$	4.5	3.5	3.5	4.5	3.5	3.5
		VAR$_3$	1.5	3.5	3.5	4.5	3.5	3.5
		VAR$_4$	4.5	3.5	3.5	4.5	3.5	3.5
		VAR$_5$	1.5	3.5	3.5	4.5	3.5	3.5
		VAR$_6$	4.5	3.5	3.5	4.5	3.5	3.5
	DTLZ6	MOEA/D	6	5.5	6	1	5.5	5.5
		VAR$_1$	6	5.5	6	2.5	5.5	5.5
		VAR$_2$	1	1	1	5.5	1	1
		VAR$_3$	2	2.5	2	5.5	3	2.5
		VAR$_4$	3.5	5.5	3.5	5.5	5.5	5.5
		VAR$_5$	3.5	5.5	6	5.5	5.5	5.5
		VAR$_6$	6	2.5	3.5	2.5	2	2.5
	DTLZ7	MOEA/D	6.5	6	6	6.5	6.5	6
		VAR$_1$	3	2.5	2.5	3	3	2.5
		VAR$_2$	3	6	6	3	6.5	6
		VAR$_3$	3	2.5	2.5	3	3	2.5
		VAR$_4$	3	2.5	2.5	3	3	2.5
		VAR$_5$	3	2.5	2.5	3	3	2.5

WFG1	**MOEA/D**	1	4	7	7	1	7
	VAR$_1$	4.5	4	3.5	3.5	4.5	3.5
	VAR$_2$	4.5	4	3.5	3.5	4.5	3.5
	VAR$_3$	4.5	4	3.5	3.5	4.5	3.5
	VAR$_4$	4.5	4	3.5	3.5	4.5	3.5
	VAR$_5$	4.5	4	3.5	3.5	4.5	3.5
	VAR$_6$	4.5	4	3.5	3.5	4.5	3.5
WFG2	MOEA/D	4.5	4	1	4	4	4
	VAR$_1$	1	4	4.5	4	4	4
	VAR$_2$	4.5	4	4.5	4	4	4
	VAR$_3$	4.5	4	4.5	4	4	4
	VAR$_4$	4.5	4	4.5	4	4	4
	VAR$_5$	4.5	4	4.5	4	4	4
	VAR$_6$	4.5	4	4.5	4	4	4
WFG3	MOEA/D	7	4.5	4	4	4	4.5
	VAR$_1$	3.5	4.5	4	4	4	4.5
	VAR$_2$	3.5	4.5	4	4	4	4.5
	VAR$_3$	3.5	4.5	4	4	4	4.5
	VAR$_4$	3.5	4.5	4	4	4	4.5
	VAR$_5$	3.5	4.5	4	4	4	4.5
	VAR$_6$	3.5	1	4	4	4	1
WFG4	MOEA/D	7	7	7	1	4.5	4
	VAR$_1$	3.5	3.5	3.5	4.5	4.5	4
	VAR$_2$	3.5	3.5	3.5	4.5	4.5	4
	VAR$_3$	3.5	3.5	3.5	4.5	4.5	4
	VAR$_4$	3.5	3.5	3.5	4.5	4.5	4
	VAR$_5$	3.5	3.5	3.5	4.5	4.5	4
	VAR$_6$	3.5	3.5	3.5	4.5	1	4
WFG5	MOEA/D	7	7	7	4	4	4
	VAR$_1$	3.5	3.5	4.5	4	4	4
	VAR$_2$	3.5	3.5	1.5	4	4	4
	VAR$_3$	3.5	3.5	1.5	4	4	4
	VAR$_4$	3.5	3.5	4.5	4	4	4
	VAR$_5$	3.5	3.5	4.5	4	4	4
	VAR$_6$	3.5	3.5	4.5	4	4	4
WFG6	MOEA/D	7	6.5	4	4	4.5	4
	VAR$_1$	3.5	3	4	4	4.5	4
	VAR$_2$	3.5	3	4	4	4.5	4
	VAR$_3$	3.5	3	4	4	4.5	4
	VAR$_4$	3.5	3	4	4	4.5	4
	VAR$_5$	3.5	6.5	4	4	1	4
	VAR$_6$	3.5	3	4	4	4.5	4
WFG7	MOEA/D	7	7	5.5	4	6	1
	VAR$_1$	3.5	3.5	5.5	4	2.5	5.5
	VAR$_2$	3.5	3.5	2	4	6	2.5
	VAR$_3$	3.5	3.5	5.5	4	2.5	5.5
	VAR$_4$	3.5	3.5	2	4	2.5	5.5
	VAR$_5$	3.5	3.5	2	4	2.5	5.5
	VAR$_6$	3.5	3.5	5.5	4	6	2.5
WFG8	MOEA/D	4.5	4	6	4	6	1
	VAR$_1$	4.5	4	6	4	2	5.5
	VAR$_2$	4.5	4	2.5	4	6	2.5
	VAR$_3$	1	4	2.5	4	4	5.5
	VAR$_4$	4.5	4	6	4	2	5.5
	VAR$_5$	4.5	4	2.5	4	2	5.5
	VAR$_6$	4.5	4	2.5	4	6	2.5
WFG9	MOEA/D	4	4	4.5	6	4	4
	VAR$_1$	4	4	4.5	2.5	4	4
	VAR$_2$	4	4	1	2.5	4	4
	VAR$_3$	4	4	4.5	2.5	4	4
	VAR$_4$	4	4	4.5	6	4	4
	VAR$_5$	4	4	4.5	6	4	4
	VAR$_6$	4	4	4.5	2.5	4	4

Based on the results obtained from experimentation, the configurations with the best performance are shown in Fig. 4 for problems with five objectives, and for problems with ten objectives are shown in Fig. 5. It was observed that the variants that provided high-quality results were

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Table 18. Ranking of problem with ten objectives, division of variables and two species

VARIANTE	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
MOEA/D	91	89.5	87.5	68.5	79	74
VAR1	57	56	64	58	57.5	62
VAR2	62.5	60	56	60	74.5	65.5
VAR3	50	59.5	53.5	63.5	57	59
VAR4	59.5	57	59.5	64.5	57.5	62
VAR5	53.5	64	55.5	67	54	62
VAR6	74.5	62	72	66.5	68.5	63.5

Table 19. Borda count of CO-MOEA/D with division by variables and four species

	PROBLEM	VARIANT	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
PROBLEMS WITH TEN OBJECTIVES. DIVISION BY VARIABLES AND FOUR SPECIES	DTLZ1	MOEA/D	6	4.5	6	5	6	6
		VAR$_1$	2.5	4.5	2.5	5	2.5	2.5
		VAR$_2$	6	4.5	6	2	6	6
		VAR$_3$	2.5	4.5	2.5	5	2.5	2.5
		VAR$_4$	2.5	4.5	2.5	5	2.5	2.5
		VAR$_5$	2.5	4.5	2.5	5	2.5	2.5
		VAR$_6$	6	1	6	1	6	6
	DTLZ2	MOEA/D	6	6	6	7	6	6
		VAR$_1$	2.5	2.5	2.5	1	2	2
		VAR$_2$	6	6	6	4	6	6
		VAR$_3$	2.5	2.5	2.5	4	2	2
		VAR$_4$	2.5	2.5	2.5	4	4	4
		VAR$_5$	2.5	2.5	2.5	4	2	2
		VAR$_6$	6	6	6	4	6	6
	DTLZ3	MOEA/D	6	4	6	4.5	6	6
		VAR$_1$	3	4	3	4.5	1.5	1.5
		VAR$_2$	6	4	6	1	6	6
		VAR$_3$	1	4	1	4.5	1.5	1.5
		VAR$_4$	3	4	3	4.5	3.5	3.5
		VAR$_5$	3	4	3	4.5	3.5	3.5
		VAR$_6$	6	4	6	4.5	6	6
	DTLZ4	MOEA/D	6	6	6	6	6	6
		VAR$_1$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_2$	6	6	6	6	6	6
		VAR$_3$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_4$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_5$	2.5	2.5	2.5	2.5	2.5	2.5
		VAR$_6$	6	6	6	6	6	6
	DTLZ5	MOEA/D	7	7	7	1	7	7
		VAR$_1$	4	4	4	4.5	3.5	3.5
		VAR$_2$	4	1	4	4.5	3.5	3.5
		VAR$_3$	1	4	1	4.5	3.5	3.5
		VAR$_4$	4	4	4	4.5	3.5	3.5
		VAR$_5$	4	4	4	4.5	3.5	3.5
		VAR$_6$	4	4	4	4.5	3.5	3.5
	DTLZ6	MOEA/D	4.5	5	4.5	2	5	5
		VAR$_1$	4.5	5	4.5	2	5	5
		VAR$_2$	1	1	1	4	1	1
		VAR$_3$	4.5	5	4.5	6	5	5
		VAR$_4$	4.5	5	4.5	6	5	5
		VAR$_5$	4.5	5	4.5	6	5	5
		VAR$_6$	4.5	2	4.5	2	2	2

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DTLZ7	MOEA/D	7	6.5	6	7	6.5	6
	VAR_1	3.5	3	2.5	3.5	3	2.5
	VAR_2	3.5	3	6	3.5	6.5	6
	VAR_3	3.5	3	2.5	3.5	3	2.5
	VAR_4	3.5	3	2.5	3.5	3	2.5
	VAR_5	3.5	3	2.5	3.5	3	2.5
	VAR_6	3.5	6.5	6	3.5	3	6
WFG1	MOEA/D	1.5	4	7	7	4	7
	VAR_1	5	4	3.5	3.5	4	3.5
	VAR_2	1.5	4	3.5	3.5	4	3.5
	VAR_3	5	4	3.5	3.5	4	3.5
	VAR_4	5	4	3.5	3.5	4	3.5
	VAR_5	5	4	3.5	3.5	4	3.5
	VAR_6	5	4	3.5	3.5	4	3.5
WFG2	MOEA/D	4	4	4	4	4	4
	VAR_1	4	4	4	4	4	4
	VAR_2	4	4	4	4	4	4
	VAR_3	4	4	4	4	4	4
	VAR_4	4	4	4	4	4	4
	VAR_5	4	4	4	4	4	4
	VAR_6	4	4	4	4	4	4
WFG3	MOEA/D	6	4	4	4	4	5.5
	VAR_1	6	4	4	4	4	5.5
	VAR_2	2.5	4	4	4	4	2
	VAR_3	6	4	4	4	4	2
	VAR_4	2.5	4	4	4	4	5.5
	VAR_5	2.5	4	4	4	4	5.5
	VAR_6	2.5	4	4	4	4	2
WFG4	MOEA/D	7	7	7	1	6	4.5
	VAR_1	3.5	3.5	3.5	4.5	6	4.5
	VAR_2	3.5	3.5	3.5	4.5	2.5	4.5
	VAR_3	3.5	3.5	3.5	4.5	6	4.5
	VAR_4	3.5	3.5	3.5	4.5	2.5	4.5
	VAR_5	3.5	3.5	3.5	4.5	2.5	4.5
	VAR_6	3.5	3.5	3.5	4.5	2.5	1
WFG5	MOEA/D	7	7	7	4	6	4
	VAR_1	3.5	3.5	3.5	4	6	4
	VAR_2	3.5	3.5	3.5	4	2.5	4
	VAR_3	3.5	3.5	3.5	4	2.5	4
	VAR_4	3.5	3.5	3.5	4	6	4
	VAR_5	3.5	3.5	3.5	4	2.5	4
	VAR_6	3.5	3.5	3.5	4	2.5	4
WFG6	MOEA/D	7	6	4	4	6	4.5
	VAR_1	3.5	2.5	4	4	6	4.5
	VAR_2	3.5	2.5	4	4	2.5	1
	VAR_3	3.5	6	4	4	2.5	4.5
	VAR_4	3.5	2.5	4	4	2.5	4.5
	VAR_5	3.5	2.5	4	4	2.5	4.5
	VAR_6	3.5	6	4	4	6	4.5
WFG7	MOEA/D	7	7	4	4	6	1
	VAR_1	3.5	3.5	4	4	3.5	4.5
	VAR_2	3.5	3.5	4	4	6	4.5
	VAR_3	3.5	3.5	4	4	1.5	4.5
	VAR_4	3.5	3.5	4	4	3.5	4.5
	VAR_5	3.5	3.5	4	4	1.5	4.5
	VAR_6	3.5	3.5	4	4	6	4.5
WFG8	MOEA/D	5.5	4	5.5	4	5	4
	VAR_1	2.5	4	5.5	4	5	4
	VAR_2	5.5	4	2	4	5	4
	VAR_3	1	4	2	4	1	4
	VAR_4	5.5	4	2	4	5	4
	VAR_5	2.5	4	5.5	4	2	4
	VAR_6	5.5	4	5.5	4	5	4
WFG9	MOEA/D	4	4	5	4.5	4	4
	VAR_1	4	4	5	4.5	4	4
	VAR_2	4	4	5	1	4	4
	VAR_3	4	4	1.5	4.5	4	4
	VAR_4	4	4	5	4.5	4	4
	VAR_5	4	4	1.5	4.5	4	4
	VAR_6	4	4	5	4.5	4	4

VAR_2 and VAR_6, both implemented with the variable-based splitting strategy. In the case of problems with ten objectives, it was observed that the VAR_6 variant, with division by objectives, showed the best performance (Table 2). Furthermore, the VAR_4 variant, with variable-based splitting, also demonstrated outstanding performance.

Table 20. Ranking of problem with ten objectives, division of variables and four species

VARIANTE	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
MOEA/D	94	89	89	71.5	85	82
VAR1	59.5	63	59	62	58	62
VAR2	62.5	51	69	60	65.5	56
VAR3	56	64.5	52.5	64.5	55	58.5
VAR4	53.5	61	49.5	64.5	52	55.5
VAR5	56	64.5	62	64.5	58.5	65
VAR6	66.5	55	67	61	71	66

Table 21. Borda count of CO-MOEA/D with division by variables and eight species

	PROBLEM	VARIANT	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
PROBLEMS WITH TEN OBJECTIVES. DIVISION BY VARIABLES AND EIGHT SPECIES	DTLZ1	MOEA/D	6	5	6	5	6	6
		VAR_1	2.5	5	2.5	5	2.5	2.5
		VAR_2	6	1.5	6	1.5	6	6
		VAR_3	2.5	5	2.5	5	2.5	2.5
		VAR_4	2.5	5	2.5	5	2.5	2.5
		VAR_5	2.5	5	2.5	5	2.5	2.5
		VAR_6	6	1.5	6	1.5	6	6
	DTLZ2	MOEA/D	6	6	6	6	6	6
		VAR_1	2.5	4	2.5	2.5	2.5	2.5
		VAR_2	6	6	6	6	6	6
		VAR_3	2.5	2	2.5	2.5	2.5	2.5
		VAR_4	2.5	2	2.5	2.5	2.5	2.5
		VAR_5	2.5	2	2.5	2.5	2.5	2.5
		VAR_6	6	6	6	6	6	6
	DTLZ3	MOEA/D	6.5	5	6.5	5	7	7
		VAR_1	3.5	5	3.5	5	3.5	3.5
		VAR_2	3.5	1.5	3.5	1.5	3.5	3.5
		VAR_3	3.5	5	3.5	5	3.5	3.5
		VAR_4	1	5	1	5	3.5	3.5
		VAR_5	3.5	5	3.5	5	3.5	3.5
		VAR_6	6.5	1.5	6.5	1.5	3.5	3.5
	DTLZ4	MOEA/D	6	6	6	6	6	6
		VAR_1	2.5	2.5	2.5	2.5	2.5	2.5
		VAR_2	6	6	6	6	6	6
		VAR_3	2.5	2.5	2.5	2.5	2.5	2.5
		VAR_4	2.5	2.5	2.5	2.5	2.5	2.5
		VAR_5	2.5	2.5	2.5	2.5	2.5	2.5
		VAR_6	6	6	6	6	6	6
	DTLZ5	MOEA/D	7	7	7	1	7	7
		VAR_1	3.5	4	4	4.5	3.5	3.5
		VAR_2	3.5	1	4	4.5	3.5	3.5
		VAR_3	3.5	4	1	4.5	3.5	3.5
		VAR_4	3.5	4	4	4.5	3.5	3.5
		VAR_5	3.5	4	4	4.5	3.5	3.5
		VAR_6	3.5	4	4	4.5	3.5	3.5
	DTLZ6	MOEA/D	5	5	5	5.5	3	3
		VAR_1	5	5	5	3	6	6
		VAR_2	1	1	1	1	1	1
		VAR_3	5	5	5	5.5	6	6
		VAR_4	5	5	5	5.5	3	3
		VAR_5	5	5	5	5.5	6	6
		VAR_6	2	2	2	2	3	3
	DTLZ7	MOEA/D	7	7	6.5	7	6	6
		VAR_1	3.5	3.5	3	3.5	2.5	2.5
		VAR_2	3.5	3.5	6.5	3.5	6	6
		VAR_3	3.5	3.5	3	3.5	2.5	2.5
		VAR_4	3.5	3.5	3	3.5	2.5	2.5
		VAR_5	3.5	3.5	3	3.5	2.5	2.5
		VAR_6	3.5	3.5	3	3.5	6	6

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WFG1	MOEA/D	2	5	6.5	7	2	6.5
	VAR_1	5.5	5	3.5	3.5	5.5	3.5
	VAR_2	2	1.5	3.5	3.5	2	3.5
	VAR_3	5.5	5	3.5	3.5	5.5	3.5
	VAR_4	5.5	5	3.5	3.5	5.5	3.5
	VAR_5	5.5	5	6.5	3.5	5.5	6.5
	VAR_6	2	1.5	1	3.5	2	1
WFG2	MOEA/D	4	4	4	4	4	4
	VAR_1	4	4	4	4	4	4
	VAR_2	4	4	4	4	4	4
	VAR_3	4	4	4	4	4	4
	VAR_4	4	4	4	4	4	4
	VAR_5	4	4	4	4	4	4
	VAR_6	4	4	4	4	4	4
WFG3	MOEA/D	7	4	6	4	5.5	7
	VAR_1	3.5	4	2.5	4	2	3.5
	VAR_2	3.5	4	6	4	2	3.5
	VAR_3	3.5	4	2.5	4	5.5	3.5
	VAR_4	3.5	4	6	4	2	3.5
	VAR_5	3.5	4	2.5	4	5.5	3.5
	VAR_6	3.5	4	2.5	4	5.5	3.5
WFG4	MOEA/D	7	7	6	1	6.5	4.5
	VAR_1	3.5	3.5	2.5	4.5	3	4.5
	VAR_2	3.5	3.5	2.5	4.5	3	1
	VAR_3	3.5	3.5	6	4.5	3	4.5
	VAR_4	3.5	3.5	2.5	4.5	3	4.5
	VAR_5	3.5	3.5	6	4.5	6.5	4.5
	VAR_6	3.5	3.5	2.5	4.5	3	4.5
WFG5	MOEA/D	7	6.5	5	4	4	4.5
	VAR_1	3.5	3	5	4	4	4.5
	VAR_2	3.5	3	5	4	4	1
	VAR_3	3.5	3	1.5	4	4	4.5
	VAR_4	3.5	3	1.5	4	4	4.5
	VAR_5	3.5	6.5	5	4	4	4.5
	VAR_6	3.5	3	5	4	4	4.5
WFG6	MOEA/D	7	6.5	6	4	7	5.5
	VAR_1	3.5	3	6	4	3.5	5.5
	VAR_2	3.5	3	2.5	4	3.5	2
	VAR_3	3.5	6.5	2.5	4	3.5	2
	VAR_4	3.5	3	2.5	4	3.5	2
	VAR_5	3.5	3	2.5	4	3.5	5.5
	VAR_6	3.5	3	6	4	3.5	5.5
WFG7	MOEA/D	7	7	4	4	6	1
	VAR_1	3.5	3.5	4	4	4	5.5
	VAR_2	3.5	3.5	4	4	6	1
	VAR_3	3.5	3.5	4	4	1	5.5
	VAR_4	3.5	3.5	4	4	1	5.5
	VAR_5	3.5	3.5	4	4	1	5.5
	VAR_6	3.5	3.5	4	4	6	1
WFG8	MOEA/D	5.5	4	4	4	5	4
	VAR_1	5.5	4	4	4	5	4
	VAR_2	5.5	4	4	4	5	4
	VAR_3	2	4	4	4	1.5	4
	VAR_4	2	4	4	4	5	4
	VAR_5	2	4	4	4	1.5	4
	VAR_6	5.5	4	4	4	5	4
WFG9	MOEA/D	4	4	4.5	4	4	4
	VAR_1	4	4	4.5	4	4	4
	VAR_2	4	4	4.5	4	4	4
	VAR_3	4	4	4.5	4	4	4
	VAR_4	4	4	1	4	4	4
	VAR_5	4	4	4.5	4	4	4
	VAR_6	4	4	4.5	4	4	4

Regarding the number of species used in these configurations, it was observed that working with 4 species had a significant impact on the quality of the solutions generated for the problems implemented.

6 Conclusions and Future Work

It can be concluded that the objective set in this work was successfully achieved through the conduct of an experimental analysis. To achieve this goal, a variety of state-of-the-art benchmark

Table 22. Ranking of problem with ten objectives, division of variables and eight specie

VARIANTE	AVG_EUCL	MIN_EUCL	AVG_TCH	MIN_TCHE	MED_EUCL	MED_TCHE
MOEA/D	94	89	89	71.5	85	82
VAR1	59.5	63	59	62	58	62
VAR2	62.5	51	69	60	65.5	56
VAR3	56	64.5	52.5	64.5	55	58.5
VAR4	53.5	61	49.5	64.5	52	55.5
VAR5	56	64.5	62	64.5	58.5	65
VAR6	66.5	55	67	61	71	66

problems were employed, providing a solid foundation for evaluating the proposed solutions. Configurations were evaluated with 2, 4, and 8 species, aiming to minimize the distance of the non-dominated set concerning the decision-maker's point of interest.

During the experimentation, parameter tuning tests were conducted on the coevolutionary algorithm, both with variable division and with objective division, allowing for the evaluation of different configurations to address multi-objective problems. It was validated that there is no single configuration that provides good solutions, but rather there are various options that can lead to viable solutions that approach the decision-maker's region of interest.

It was observed that variable division and four species predominated. Additionally, it was highlighted that the VAR_6 variant excels for both five and ten objectives. Therefore, it could be considered that VAR_6, along with a strategy of objective or variable division and 4 species, maybe a viable configuration that offers good results.

As a future work, it would be interesting to expand this study into a dynamic environment, where the parameters and/or conditions of the problem may change over time. This would allow evaluation of how the adaptability of the cooperative coevolutionary algorithm impacts the quality of the solutions generated concerning the DM's region of interest. Such an approach could provide a more comprehensive understanding of the algorithm's effectiveness in real-world situations where conditions may change unexpectedly.

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