# Overview of Artificial Immune Systems for Multi-objective Optimization

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**Abstract.** Evolutionary algorithms have become a very popular approach for multiobjective optimization in many fields of engineering. Due to the outstanding performance of such techniques, new approaches are constantly been developed and tested to improve convergence, tackle new problems, and reduce computational cost. Recently, a new class of algorithms, based on ideas from the immune system, have begun to emerge as problem solvers in the evolutionary multiobjective optimization field. Although all these immune algorithms present unique, individual characteristics, there are some trends and common characteristics that, if explored, can lead to a better understanding of the mechanisms governing the behavior of these techniques. In this paper we propose a common framework for the description and analysis of multiobjective immune algorithms.

## 1 Introduction

Multiobjective problems arise in many engineering and scientific applications, where many conflicting goals have to be achieved simultaneously. In this class of problems, evolutionary algorithms in general have been demonstrated to be an effective and efficient tool for finding the set of trade-off solutions that characterize the Pareto-optimal set. For a good overview of the current state-of-art in multiobjective evolutionary techniques, we refer to some of the main books in the field[21,8,37] and also to the Online EMO Repository [11].

During the last decade [16], a new paradigm based on principles of the immune system has been employed for developing interesting algorithms for both mono and multiobjective optimization (MOO). Artificial immune systems (AIS) [20] have found applications in many fields such as pattern recognition, computer defense, optimization, and others. Since then, many multiobjective AIS algorithms have appeared in a variety of conference proceedings and technical journals, some of them not specialized in evolutionary computation. The main objective of this paper is to present a broad overview of the current MO-AIS techniques available in literature. Performance comparisons, however, are outside of the scope of this work, due to space constraints. This paper proposes a

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common framework for MO-AIS algorithms, presenting a canonical MO-AIS algorithm from which all other MO-AIS algorithms reviewed can be instantiated. This common framework can simplify the comparative analysis of the algorithms, as well as the introduction of new characteristics and the study of their effects. Finally, we discuss the employment of other AIS principles in the improvement of multiobjective techniques, and present a brief overview of other immunological principles that could be employed for the development of new algorithms.

## 2 Multiobjective Optimization and the Immune System

In multiobjective optimization, we consider the following general problem:

$$\begin{array}{c} \mathcal{X}^* = \arg\min f(x) \\ \text{subject to: } x \in \mathcal{F} \subseteq \mathcal{X} \end{array} \tag{1}$$

in which $x \in \mathcal{X}$ represents the optimization variables. The objective functions are $f : \mathcal{X} \mapsto \mathbb{R}^m$, that is, they map the optimization variables into real values. The set $\mathcal{F}$ represents the feasible set, mathematically defined as:

$$\mathcal{F} = \{x \in \mathcal{X} : g(x) \leq 0\} \tag{2}$$

where $g : \mathcal{X} \mapsto \mathbb{R}^p$ are the constraint functions. If the problem is unconstrained, $\mathcal{F}$ and $\mathcal{X}$ are equivalent.

In the multiobjective context, there is not only one solution, but a set of trade-off or Pareto-optimal solutions defined as:

$$\mathcal{X}^* \triangleq \{x \in \mathcal{F} : \nexists z \in \mathcal{F} | f(z) \leq f(x), f(z) \neq f(x)\} \tag{3}$$

Since $f(z)$ and $f(x)$ are vectors in $\mathbb{R}^m$, we need to define the relational operators $\leq$ and $\neq$:

$$f(z) \leq f(x) \Leftrightarrow f_i(z) \leq f_i(x), \forall i = 1, \ldots, m \tag{4}$$

$$f(z) \neq f(x) \Leftrightarrow \exists i = \{1, \ldots, m\} : f_i(z) \neq f_i(x) \tag{5}$$

The evolutionary multiobjective techniques are designed to find a set of non-dominated solutions that best represents the Pareto-optimal set. The search is performed through the consecutive application of stochastic and heuristic operators, balancing global and local search capabilities, over a population of candidate solutions. For a good overview of evolutionary multiobjective algorithms, see References [21,8].

Figure 1 shows the outline of a general population-based algorithm. This algorithm presents the fundamental ingredients for designing an evolutionary multiobjective technique, with the implementation details of each operator (e.g., whether the initialization procedure is random or deterministic, or the way to implement the Selection) varying from one algorithm to another.