Multiobjective optimization and Artificial Immune System: a review

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ABSTRACT

The Chapter aims to review the state-of-the-art in multiobjective optimization with Artificial Immune System algorithms. As it will be focused in the Chapter, artificial immune systems have some intrinsic characteristics which make them well suited as multiobjective optimization algorithms. Following this basic idea, different implementations have been proposed in the literature. This Chapter aims to provide a thorough review of the literature on multiobjective optimization algorithms based on the emulation of the immune system.

INTRODUCTION

Many real world problems involve the simultaneous optimization of various and often conflicting objectives. Evolutionary algorithms seem to be the most attractive approaches for this class of problems, because they are usually population based techniques that can find multiple compromise solution in a single run, and they do not require any hypotheses on the objective functions (e.g. unimodality and convexity). Among other techniques, in the last decade a new paradigm based on the emulation of the immune system behaviour has been proposed. Since the pioneer works, many different implementations have been proposed in the literature. The aim of this Chapter is to review the most significant works in this field, giving a common framework for classification and showing strengths and weaknesses of artificial immune system metaphor in multiobjective optimization with respect to other bio-inspired algorithms.

The Chapter is structured as follows. Section 3 gives a background on the immune system and multiobjective optimization terminology used in the Chapter. Section 4 explains the methodology used to select the reference list used for the review, while in Section 5 the papers are reviewed according to their research field. Finally in Section 6 future and emerging trends in multiobjective optimization with artificial immune systems are drawn.

BACKGROUND

Immune System overview

Our immune system has as its main task the detection of the infectious foreign elements (called pathogens) that attack us, and defend us from them (in other words, its main task is to keep our organism healthy). Examples of such pathogens are bacteria and viruses. Any molecule that can be recognized by our immune system is called antigen. Such antigens provoke a specific response from our immune system. Lymphocytes are a special type of cells that play a major role in our immune system. Two types of lymphocytes exist: B cells (or B lymphocytes) and T cells (or T lymphocytes). Upon detection of an antigen, the B cells that best recognize (i.e., match) the antigen are cloned. Some of these cloned cells will be differentiated into plasma cells, which are the most active antibodies secretors, while others will act as memory cells. These cloned cells are subject to a high somatic mutation rate (normally called hypermutation) in order to increase their affinity level (i.e., their matching to the antigens). These mutations experienced by the clones are proportional to their affinity to the antigen. The highest affinity cloned cells experiment the lowest mutation rates, whereas the lowest affinity cloned cells have high mutation rates. Due to the random nature of this mutation process, some clones could be dangerous to the body and are, therefore, eliminated by the immune system itself. Plasma cells are capable of secreting only one type of antibody, which is relatively specific for the antigen. Antibodies play a key role in the immune response, since they are capable of adhering to the antigens, in order to neutralize and eliminate them.

These cloning and hypermutation processes are collectively known as the clonal selection principle. It is worth noting, however, that the immune response is certainly more complex than the above explanation, in which we only focused on the B cells, in order to keep our discussion very short.

Once the antigens have been eliminated by the antibodies, the immune system must return to its normal conditions, eliminating the in-excess cells. However, some cells remain in our blood stream acting as memory cells, so that our immune system can ‘remember’ the antigens that have previously attacked it. When the immune system is exposed again to the same type of antigen (or a similar one), these memory cells are activated, presenting a faster (and perhaps improved) response, which is called secondary response.

Based on the previous (oversimplified) explanation of the way in which our immune system works, we can say that, from a computer science perspective, the immune system can be seen as a parallel and distributed adaptive system. Clearly, the immune system is able to learn, it has memory, and is able of tasks such as associative retrieval of information. These features make immune systems very robust, fault tolerant, dynamic and adaptive. All of these properties make it very attractive to be emulated in a computer.

Artificial Immune Systems (AIS) are composed of the following basic elements:

- A representation for the components of the system (e.g., binary strings, vectors of real numbers, etc.).
- A set of mechanisms to evaluate the interaction of individuals with their environment and with each other. Such an environment is normally simulated through an affinity function, which is based on the objective function(s) in the case of optimization problems.
- Procedures of adaptation, that indicate the way in which the behavior of the system changes over time. These procedure of adaptation consist of, for example, mutation operators.

AISs are population-based metaheuristics, and have been widely used for a wide variety of optimization and classification tasks.

Multiobjective optimization

Multiobjective optimization refers to the simultaneous optimization of two or more objectives, which are normally in conflict with each other. Formally, we are interested in the solution of problems of the form:

$$\text{minimize } \left[f_1(\vec{x}), f_2(\vec{x}), \ldots, f_k(\vec{x}) \right] \tag{1.1}$$

subject to the m inequality constraints:

$$g_i(\vec{x}) \leq 0 \quad i = 1, 2, \ldots, m \tag{1.2}$$

and the p equality constraints:

$$h_i(\vec{x}) = 0 \quad i = 1, 2, \ldots, p \tag{1.3}$$

where k is the number of objective functions $f_i : \Re^n \to \Re$. We call $\vec{x} = [x_1, x_2, \ldots, x_n]^T$ the vector of decision variables. We wish to determine from among the set F of all vectors which satisfy (1.2) and (1.3) the particular set of values $x_1^*, x_2^*, \ldots, x_n^*$ which yield the best compromise solutions among all the objective functions.

Pareto Optimality

The most commonly notion of optimality adopted in multi-objective optimization is the so-called Pareto optimality (Pareto, 1896), which is the following:

We say that a vector of decision variables $\vec{x}^* \in F$ is Pareto optimal if there does not exist another $\vec{x} \in F$ such that $f_i(\vec{x}) \leq f(\vec{x}^*)$ for all $i = 1, \ldots, k$ and $f_j(\vec{x}) < f(\vec{x}^*)$ for at least one j (assuming minimization).

In words, this definition says that $\vec{x}^*$ is Pareto optimal if there exists no feasible vector of decision variables $\vec{x} \in F$ which would decrease some criterion without causing a simultaneous increase in at least one other criterion. Unfortunately, this concept almost always gives not a single solution, but rather a set of solutions called the Pareto optimal set. The vectors $\vec{x}^*$ corresponding to the solutions included in the Pareto optimal set are called nondominated. The image of the Pareto optimal set under the objective functions is called Pareto front.

The aim in multiobjective optimization is to find the elements of the Pareto optimal set (normally, as many different elements, as possible). In the Operations Research literature, a number of mathematical programming techniques have been proposed to solve multiobjective optimization problems. However, such techniques normally require an initial point to trigger the search, and tend to produce a single element of the Pareto optimal set per run. Additionally, they are normally susceptible to the shape and continuity of the Pareto front. On the other hand, population-based metaheuristics (such as evolutionary algorithms and artificial immune systems), are less affected by the features of the Pareto front and can generate several elements of the Pareto optimal set in a single run, departing from a randomly generated population.

For a good motivation for multiobjective optimization and a thorough description of the multiobjective optimization algorithms cited in this chapter, the reader should refer to the suggested readings included at the end of the chapter. The bibliography is limited to the reviewed papers, only.

METHODOLOGY

The selection of reviewed papers has been done by accessing to Compendex and Inspect scientific databases, using as keywords

a) multiobjective (or multi-objective) AND immun* (* is truncation wildcard),

b) multiobjective (or multi-objective) AND clonal.

Only papers in English language published by December 2007 have been considered. In addition references from the EMOO repository (http://delta.cs.cinvestav.mx/~ccoello/EMOO) have been selected by searching with immun and clonal as keywords. Finally, results have been manually filtered to avoid false positive matching. The total number of reference found so far is 80. The distributions of the references by year and by category are shown in Figure 1 and Figure 2, respectively.

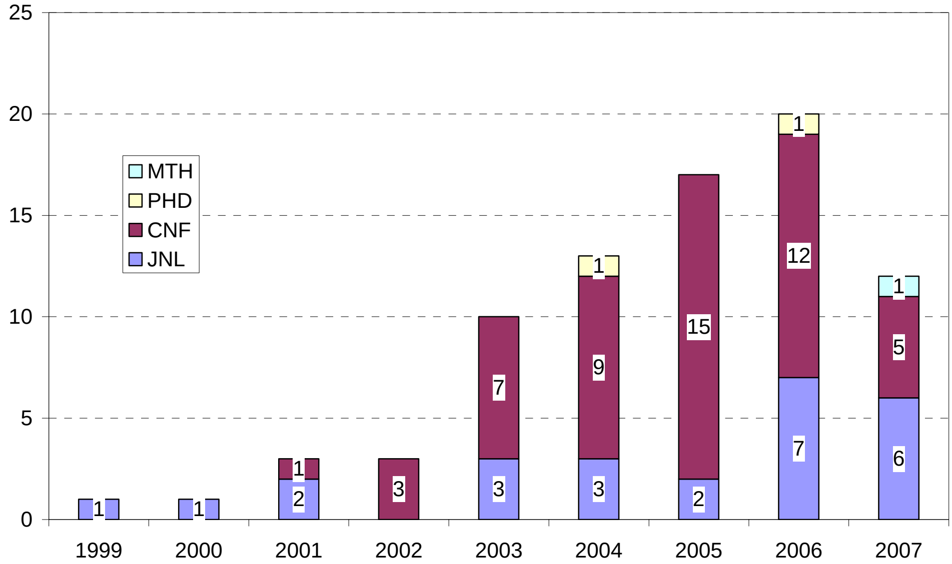

Figure 1: Distribution of the references by year (MTH: Master thesis, PHD: PhD Thesis, CNF: Conference Paper, JNL: Journal Paper).

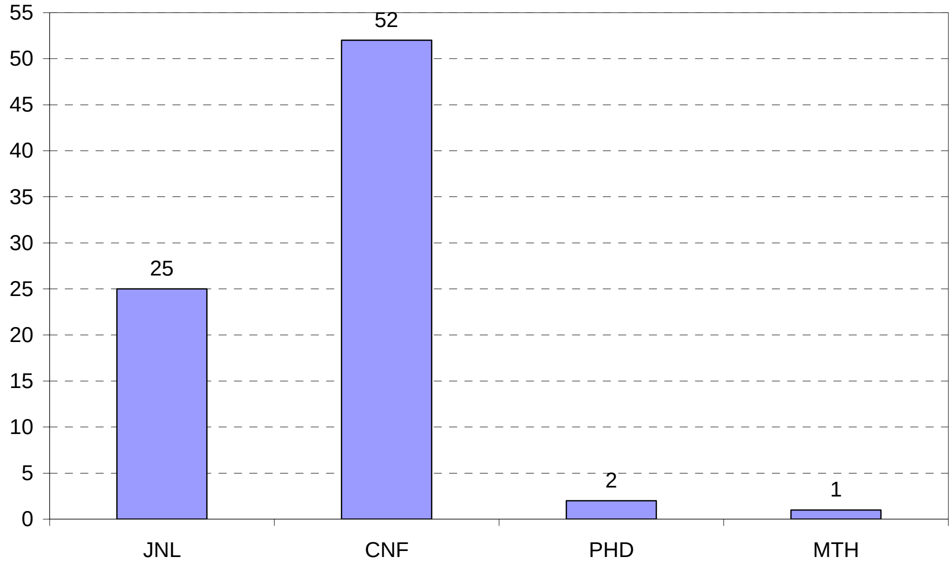

Figure 2: Distribution of the references by category (MTH: Master thesis, PHD: PhD Thesis, CNF: Conference Paper, JNL: Journal Paper).

It is worth noting that the distribution by year of Figure 1, approximatively reflects the same trend of the distribution of references on multiobjective optimization available on the EMOO repository, with a peak delay of one year (2005 EMOO repository, 2006 this work), testifying the more recent development of MOAIS with respect to other evolutionary multiobjective heuristics.

CLASSIFICATION

In the present analysis, references are classified by their research field (see Figure 3):

- Survey papers (SUR): general reviews or review on some specific field
- Algorithmic papers (ALG): papers describing the implementation of AIS for multiobjective optimization
- Theoretical papers (THE): theoretical works on multiobjective AIS optimization
- Papers on hybrid algorithms (HYB): propose hybridization of other heuristics by AIS
- Application paper (APP): show the application of MOAIS to some specific topic
- Analogy papers (ANA): show analogies between Artificial Immune System and other metaphors;

The reference list collect two PhD Theses (Chueh, 2004; Freschi, 2006) and one Master Thesis (Haag, 2007a). Since they are usually multi purposes and they are not easily available for the scientific community, they are not reviewed in this work. The content of these unpublished thesis can be found in regular papers by the same Authors.

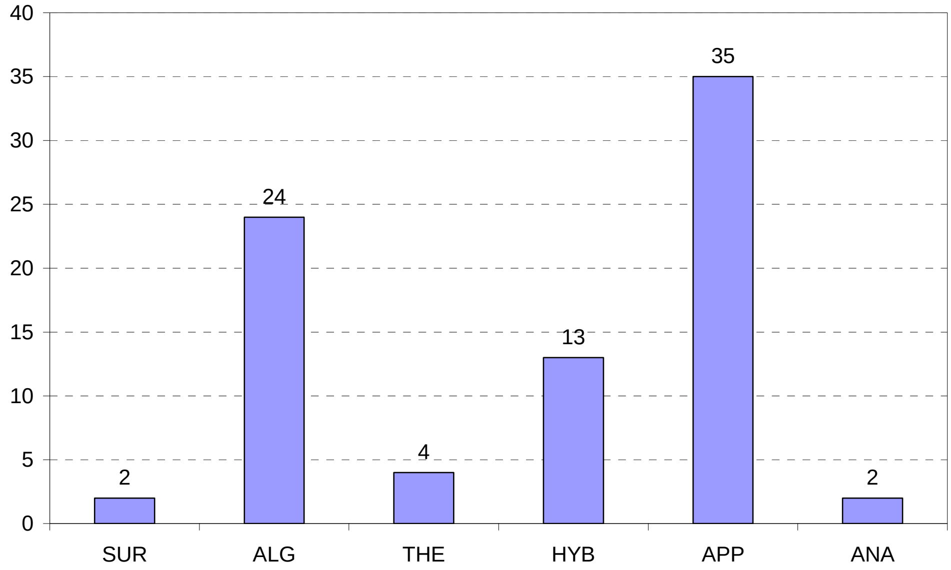

Figure 3: Distribution of references by application field (see text for abbreviations). Note that one paper may belong to different fields.

MOAIS Surveys

The work classifying the state of the art of MOAIS starts very recently. Two works only appear within the selected references. Campelo, Guimarães, & Igarashi (2007) provided a common framework for the description and analysis of MOAIS, presenting a canonical MOAIS algorithm from which other algorithm can be reviewed. Darmoul, Pierreval & Gabouj (2006) propose a more specific review reporting the use of single and multiobjective AIS for scheduling problems. With respect to these interesting reviews, our work tries to take into account not only original MOAIS algorithms but also their different fields of application.

MOAIS Algorithms

The first direct use of the immune system for multiobjective optimization goes back to Yoo & Hajela (1999). In their work they use a standard genetic algorithm where the immune principle of antibody-antigen affinity is employed to modify the fitness value. In a first time the population is evaluated versus the problem objectives and different scalar values are obtained by making reference to different weighting combinations. The best individual with respect to each combination is identified as antigen. The rest of the population is the pool of antibodies. Then antibodies are matched against antigens by the definition of a matching score. The best matching antibody fitness is added by this matching score, evolving the population of antibodies to cover antigens. In a subsequent work (Yoo & Hajela, 2001) fuzzy logic is adopted instead of weighting approach.

Besides the importance of pioneer work of Yoo and Hajela, their algorithm cannot be properly considered as a MOAIS.

For the following classification we adopt the common outline of the canonical MOAIS proposed in (Campelo, Guimarães, & Igarashi, 2007), reported in Figure 4.

```
0.  define search space Ω, population size N, objectives and constraints
1.  initialize population
2.  initialize memory
3.  while stop criterion is not met
    a.     evaluate objectives and constraints
    b.     evaluate avidity (scalar index for ranking)
    c.     select clone set
    d.     cloning and mutation
    e.     suppression (diversity enforcement)
    f.     update population
    g.     update memory
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Figure 4: Outline of the canonical MOAIS. Adapted from (Campelo, Guimarães, & Igarashi, 2007).

MISA

The multiobjective immune system algorithm (MISA) can be considered the real first proposal of MOAIS in literature (Coello Coello & Cruz Cortés, 2002). In the first proposal of the algorithm, Authors attempted to follow the clonal selection principle very closely, then the algorithm performances have been improved in a successive version (Cruz Cortés & Coello Coello 2003a, 2003b; Coello Coello & Cruz Cortés, 2005) sacrificing some of the biological metaphor. The population is encoded by binary strings and it is initialized randomly. The algorithm does not use explicitly a scalar index to define the avidity of a solution but some rules are defined for choosing the set of antibodies to be cloned. The ranking scheme uses the following criteria 1) first feasible and nondominated individuals, then 2) infeasible nondominated individuals, finally 3) infeasible and dominated. The memory set (called secondary population) is updated by the nondominated feasible individuals. Because of this repository being limited in size, an adaptive grid is implemented to enforce a uniform distribution of nondominated solutions. The number of clones for the pool of best antibodies depend on the antibody-antibody affinity. These best antibodies are selected for a uniform mutation, with mutation probability proportional to antibody-antigen affinity, according to the ranking scheme previously described, while the remaining population undergoes a nonuniform mutation. Again, the ranking scheme is used as criterion to reduce the population to its original cardinality.

MOIA

Luh, Chueh & Liu (2003) develop the multiobjective immune algorithm (MOIA). In MOIA antibodies are encoded as binary strings with a distinction of light chains (least significant bits) and heavy chains (most significant bits). Objectives are evaluated and the rank index, which measures the dominance level, is defined. Nondominated antibodies are chosen for hypermutation, that take places only in light chain, to ensure only local mutations. After this phase, nondominated cells are stored into memory. Suppression and generation of the new antibody population is a complex step in MOIA. Firstly a cumulative scalar index, named avidity, is evaluated as a product of antibody-antigen affinity (reciprocal of rank index) and antibody-antibody affinity (reciprocal of a distance measure). This combined index is used to select antibodies for the construction of germ-line DNA libraries, that requires also a predefined percentage of memory cells. Then, through a recombination/diversification stage the population for the next iteration is created.

Authors extend their work for handling constraints in a successive paper (Luh & Chueh, 2004). The problem is transformed into an unconstrained one by associating to each antibody an interleukine value. In biological processes interleukine can either stimulate or suppress the promotion of antibodies. In their in silico experiments, the interlukine is a global index of constraint violation which is summed to the rank index.

MOCSA

Multiobjective clonal selection algorithm (MOCSA) is the real coded multiobjective version of clonalg (Campelo, Guimarães, Saldanha, Igarashi, Noguchi, Lowther & Ramirez, 2004). Antibodies are evaluated over the objectives and classified by a nondominated sorting, i.e. individuals are ranked into successive nondominated fronts. Then clones are generated for whole population; the number of clones for each antibody is inversely proportional to its ranking index. A random perturbation with fixed standard deviation is then added to clones, in order to locally explore the search space. The whole population of original antibodies and mutated clones is ranked in fronts and copied into memory. Then suppression is applied, according to a niching procedure in objective space. At each iteration s given percentage of randomly generated antibodies are allowed to replace the lower ranked antibodies, ensuring the maintenance of diversity in the population.

VIS

Freschi & Repetto (2005, 2006) extend the optimization ability of opt-aiNet to multiobjective problems. Their algorithm, named vector immune system (VIS), has two nested loops: the clonal selection stage is repeated a certain number of times, before evaluating interactions in the antibody network.

The scalar index is based on simple a Pareto ranking: avidity of each antibody is the number of antibody by which it is dominated. Since VIS deals with real coded variables, the hypermutation operator is obtained by a random perturbation with standard deviation that depends on the avidity value and it is adapted by the 1/5 success rule. The selection mechanism does not consider the whole population, but each time the best antibody among a parent and its progenies is selected. It is worth noting that in this stage a dominated solution has opportunities to evolve, preventing a faster convergence to local optimal fronts. Memory is updated at this stage by copying nondominated cells into memory. Diversity is enforced after a predefined number of cloning/selection steps into the memory pool, by evaluating antibody-antibody affinity in objective space and then removing most affine solutions from memory by using an adaptive suppression threshold. As in MOCSA, at each iteration a fixed number of newcomers is allowed to enter the population. In addition Authors suggest an original constraint handling technique which maintains the feasibility of solutions during mutation, which can be adopted any time the constraint evaluation is not time consuming.

IDCMA

The immune dominance clonal multiobjective algorithm (Jiao, Gong, Shang, Du & Lu, 2005) introduces the concept of immune differential degree as measure of antibody-antibody affinity. This index is used to reduce the size of nondominated antibodies in the memory before the cloning stage. One random antibody is selected from the memory and it is used to activate a new population of random antibodies generated at each iteration. These antibodies are sorted by their affinity with the activation antibody (based on the degree of matching bits in strings) and are split into two sets: dominance clonal antibody population and immune anergy antibody population. The former set undergoes to recombination and binary mutation and it is recombined with the latter set and to memory to provide the population for the next iteration. Since variables are coded as binary strings, the extension to combinatorial problems is straightforward and presented successively in Ma, Jiao, Gong & Liu (2005).

IFMOA

The same Authors of IDCMA propose the immune forgetting multiobjective optimization algorithm (IFMOA) (Lu, Jiao, Du & Gong, 2005) for problems with real variables. In this case avidity is a scalar index which contains both Pareto dominance and density information. Antibody-antigen affinity is measured by Pareto strength, as in the strength Pareto evolutionary approach, while antibody-antibody affinity is inversely proportional to the sum of two smallest Euclidean distances between an antibody and the rest of population. The immune forgetting operator is introduced to emulate the non activation of certain cells when exposed to antigens. Part of the evolved population is suppressed (according to the avidity value) and replaced by antibodies from the memory.

CSADMO/ICMOA

A further work of Shang, Jiao, Gong & Lu (2005) extends the previous ideas to continuous dynamic multiobjective optimization problems. The clonal selection algorithm for dynamic multiobjective optimization (CSADMO) implements the nonuniform mutation, which combines the mutation operator with information on the evolutionary generation: the more the algorithm approaches to its termination, the smaller the mutation amplitude. To enforce diversity, when nondominated antibodies exceed a fixed threshold, suppression operator is applied to the population according to the crowding distance criterion already proposed for the nondominated sorting genetic algorithm (NSGA-II). It is important to notice that in CSADMO no particular strategies are adopted to solve dynamic problems, but the algorithm only exploits the natural ability of the immune system to adapt dynamically to the problem.

Immune clonal multiobjective algorithm (ICMOA) is very similar to CSADMO and it is proposed to study ZDT problems (Shang & Ma, 2006) and 0/1 knapsack problems (Shang, Ma & Zhang, 2006).

Tan & Mao's MOIA

Tan & Mao (2005) proposed the use of an aggregating function based on compromise programming (Miettinen, 1998) to solve multiobjective optimization problems. The aggregating function adopted requires the maximum and minimum values in each objective, and it is not clear from the paper if they adopt the local maxima and minima of each iteration, or if they require the user to obtain the ideal vector (i.e., the optimum values for each objective, considered separately). If such an ideal vector is required, that increases the computational cost of the algorithm, since additional single-objective optimizations need to be performed. This approach uses immune network theory for the search engine, and it is appropriately called Multi-objective Optimization based on Immune Algorithm (MOIA). The authors advocate for the advantages of their approach over traditional Pareto ranking and density estimation schemes. However, the authors provide no discussion regarding two parameters introduced: suppression threshold and decay scale.

PAIA

In their population adaptive based immune algorithm (PAIA), Chen & Mahfouf (2006) emulate the adaptivity of antibody concentration in the blood with an adaptive population size in their algorithm. The main characteristic of PAIA is the activation process. Starting from one random antibody chosen in the population, two affinity measures are calculated for dominated and nondominated solutions. These values are related to the distance from the identified antibody in the search space and they are defined to ensure that nondominated antibodies always have smallest affinity. The index defined so far couple information about antibody-antibody and antibody antigen affinities. The clone set is selected with reference to affinity, then a variable number of clones is generated, specifying the total number of clones allowed. The unselected antibodies are cloned once. Mutation is a random perturbation with standard deviation proportional to the parents' affinity. At the end of the iteration suppression is applied to the population for antibodies whose distance from other solutions is greater than a predefined network threshold.

PAIA does not implement an external offline population to collect memory cells, but evolve nondominated antibodies by maintaining them in the population, dynamically adapted to the complexity of the problem.

omni-aiNet

Coelho & Von Zuben (2006) put their algorithm, based on immune network theory, within the framework of an omni-optimization, where the same algorithm can solve single and multiobjective optimization, both constrained and unconstrained. omni-aiNet works with a real coded population and it incorporates two genetic variation techniques: polynomial mutation and gene duplication. Polynomial mutation is the mechanism that governs the hypermutation mechanism with a mutation rate inversely proportional to the avidity. Avidity is evaluated according to the constrained ε-dominance rank index. The selection process make reference to a grid procedure for selecting antibodies with a good spread in the objective space, contributing to the diversity of solutions in the population. Then gene duplication is applied to the population: a random coordinate is selected and its value is used to replace other coordinate whenever this replacement improves the performance of the antibody. The suppression is based on the Euclidean distance in variable space, applying binary tournament for too close antibodies. The rules for binary tournament are based on constraint violation. Finally random newcomers are introduced at each iteration. The cardinality of the population is not defined a priori, but it is dynamically adjusted by the algorithm during the evolution, according to the suppression threshold.

ACSAMO

In their adaptive clonal selection algorithm for multiobjective optimization (ACSAMO), Wang & Mahfouf (2006) keeps trace of two best solutions that act as antigens: the best previous population and the best overall solution in the actual population. To identify these best solutions it is used a dynamically adjusted weighted approach, with weights randomly changed at each iteration. The avidity of an antibody is then defined as the sum of its Euclidean distances from antigens (best previous population and the best overall solution) measured in the search space. This index is used also to drive the mutation amplitude, so that the best the individual, the shorter the mutation. The selection of cells for the next generation is based on nondominated sorting and, with the eventual suppression of exceeding antibodies by the light of the crowding distance indicator. The offline memory is added by the nondominated antibodies

CNMOIA

In his constrained nonlinear multiobjective optimization immune algorithm (CNMOIA), Zhang (2006, 2007) computes two scalar indicators for each antibody: antibody-antigen affinity and antibody density. The first value measures the proximity to nondominated solutions by means of the definition of an inner product and it is suitably coupled with the constraint violation degree. The second one counts the number of solutions in the proximity of the antibody. These information contribute to create also a scalar index which measure the stimulation level of an antibody. The number of clones for each antibody and its mutation probability are evaluated according to the affinity value, while antibodies are dynamically selected for the next generation with a probability which depends on the stimulation level. In CNMOIA, memory coincides with antigen population.

QUICMOA

Li & Jiao (2007) propose to merge quantum theory with the immune metaphor in their quantum inspired immune clonal multiobjective optimization algorithm. They use a novel probabilistic representation of antibodies, based on the concept of quantum bits (qubits). One qubit is defined with a pair of complex numbers that give the probability that the qubit will be found in the 0 or 1 state. A qubit may be in the 1 state, in the 0 state, or in a linear superposition of the two. The rationale of this encoding is that qubits have better characteristic of diversity than binary encoding, since a single qubit is enough to represent four states, when two bits are needed in the classical representation. The additional expenses is the decoding phase of qubits given by the observing operator. According to the solution representation, Authors propose recombination update and chaos update strategy as search technique. The rest of the algorithm is similar to ICMOA and other algorithm based on clonal selection with binary variables.

Discussion

In this section the main features which have been recognized by authors as additional strength of MOAIS over other bio inspired algorithms are presented.

Diversity enforcement. Basically MOAIS algorithms belong to two macro-groups. Algorithms based on the clonal selection principle and algorithms based on immune network theory. The latter are structured in order to make independent parallel searches of optimal solutions, leaving to an upper level of the algorithm the management of suppression of similar configurations. This feature prevent genetic drift toward a portion of the Pareto front. Population based algorithms must introduce ad hoc tricks to prevent premature convergence, such as niching, fitness sharing, etc.

Elitism. In population based algorithms the population is usually replaced by offspring after mating. Elitism must be introduced to preserve good solutions and not lose them during iterations. Elitism is inherently embedded in the selection scheme of AIS, whichever set is chosen for selection (parent, clones, memory cells, or union of these sets). This is a common feature of almost all implementation of MOAIS.

Adaptive population. State-of-the-art multiobjective optimization algorithms work with a population of fixed size. One peculiarity of MOAIS is the possibility of adjust the cardinality of the population with the problem (Coelho & Von Zuben, 2006 and Chen & Mahfouf, 2006), according to a predefined suppression threshold. The presented results show that whatever initial size is used, the population is adaptively adjusted to a reasonable size for the specific problem. This feature leads to two advantages: the population size is not a crucial parameter and the number of objective function calls is reduced to the minimum.

Clone size. In a similar way, also the hypermutation operator can be designed in such way that the number of clones for each antibody can be variable, depending on the Pareto ranking (as in MISA, VIS, PAIA).

Memory. The archive of best solutions found during iterations is considered as a key point for the success of multiobjective algorithms. While other evolutionary algorithm have to artificially introduce a fictitious repository for nondominated solutions, the memory mechanism is already defined in MOAIS and optimal solutions are simultaneously preserved once located. Memory can be external (as in MISA, MOIA, VIS) or part of the population, after having applied the suppression operator. This issue could be very effective in tackling dynamic optimization problems.

Comparisons of MOAIS

Comparisons among different MOAIS algorithms and among MOAIS and other bio inspired metaphors is not a standardized task and it is difficult to perform. Most of the source codes of reviewed algorithms are not available for the scientific community neither by request to the authors. Obviously in most of the papers some comparisons are carried out with other state-of-the-art algorithms, using standard test functions and standard metrics. In some cases these comparisons seem to be unfair, e.g it is not clear whether the number of objective function calls is equal for all algorithms.

By a deep analysis of all tests reported by developers, it comes out that only low dimensional test cases have been analyzed (up to four objective functions) but also with very high decision spaces (up to 750 binary variables). The overall performances are shown to be good (MOAIS are capable to converge to the true Pareto front) but no final conclusions can be drawn.

Theory of MOAIS

Despite the considerable effort in developing algorithms based on the IS metaphor, both single and multi objective, there is little work on theory of convergence in literature. To our best knowledge, the very first attempt to provide a mathematical background of convergence of a MOAIS algorithm is (Villalobos-Arias, Coello Coello & Hernandez-Lerma, 2004). The main result is the mathematical proof with Markov chains theory of convergence of MISA (with binary representation of variables and uniform mutation operator) under the hypothesis of using elitism, a secondary population which stores the nondominated solutions in their specific case. In (Villalobos-Arias, Coello Coello & Hernandez-Lerma, 2005) the same Authors removed some constraints on the way of transition from one state to another, giving a more general proof of convergence of a MOAIS. Zhang (2006, 2007) provided the proof of weak convergence of CNMOIA (with real or binary encoding and nonlinear constraints) for any initial antibody population distribution, by using inhomogeneous Markov chains.

Hybridization of MOAIS

Some immune principles are often used in literature to hybridize other metaheuristics, in order to best-fit a particular problem or to increase a particular feature during the evolution.

Cui, Li & Fang (2001) proposes the emulation of the self adaptive mechanism that keep immune balance, i.e. control the production of similar antibodies to preserve diversity. They propose a strategy based on immunity and entropy to evaluate affinity among antibodies and penalize more similar individuals by exponential fitness rescaling which reduce their reproduction probability. They apply the methodology to a multiobjective genetic algorithm for the solution of a flow shop scheduling problem.

The hypermutation mechanism seem to be very attractive to increase the exploitation phase during the evolution. Cutello, Narzisi, & Nicosia, (2005) for example, improve the performances of the (1+1) Pareto archived evolutionary algorithm (PAES) by two hypermutation operators, used together in the affinity maturation phase: the first one may change dramatically the individual by randomly replacing one variable, the second one performs a local search in the proximity of the parent. Results shows that the hybrid approach outperforms the standard PAES, with a computational effort similar to single objective state-of-the-art approaches for the Protein Structure Prediction problem. Zhang.; Meng & Jiao (2005a , 2005b) and Meng, Zhang & Liu (2005) hybridize a multiobjective particle swarm algorithm by the use of clonal selection operator. The balance between competition and clonal selection is designed to provide an appropriate selection pressure to the swarm population. Comparisons are performed versus the multiobjective particle swarm optimization (MOPSO) algorithm on standard metrics with better performances. Kurapati & Azarm (2000), couple the immune network simulation with a multiobjective genetic algorithm in a two level algorithm. During the first step the system is hierarchical decomposed in subsystems, which handles a portion of the overall design vector. Each system is solved for the same set of objective functions, but optimize different variables. The immune network simulation is used to provide a coordination strategy for subsystems by evaluating affinity among nondominated solutions in each subsystem.

The concept of vaccination is used by Meng & Liu (2003) to restrain degeneracy of the evolution process. At each iteration, through a detailed analysis of nondominated solutions, common information are extracted and used to modify some individuals produced by the standard strength pareto evolutionary algorithm.

Balicki & Kitowski (2003) and Balicki, (2004, 2005), present an hybridization of a tabu search algorithm with a model of the immune system to handle constraints in multicriteria optimization problems. A negative selection algorithm is used to handle constraints by subdividing the population into two groups: feasible-antigens and infeasible-antibodies. The amount of similarity at the genotype level between antibodies and a randomly chosen antigen is used as fitness of a internal procedure, responsible of producing feasible individuals for the external tabu search algorithm. The procedure is proposed to solve the task assignment in distributed computer system problem, improving the quality of the outcomes obtained by the standard algorithm.

The reverse hybridization process is also present in literature, i.e. using features from other metaphors to hybridize AIS algorithms. In Ahuja, Das & Pahwa (2007) a multiobjective clonal selection algorithm is combined by ant colony optimization: to exploit the information gathered from previous iterations, Authors use a pheromone-based hypermutation method to improve the balance between exploration and exploitation, but no comparisons are presented neither with a pure AIS nor with other algorithms. Tavakkoli-Moghaddam, Rahimi-Vahed & Mirzaei (2007a, 2007b) hybridize the clonal mutation operator by borrowing antibodies improvement methods from bacterial optimization. Bacterial mutation and gene transfer are applied as mutation operators.

Application fields of MOAIS

Application of MOAIS algorithms to real world problems largely diffused in the reviewed references. In the following these papers are organized by their field of application, as shown in Figure 5.

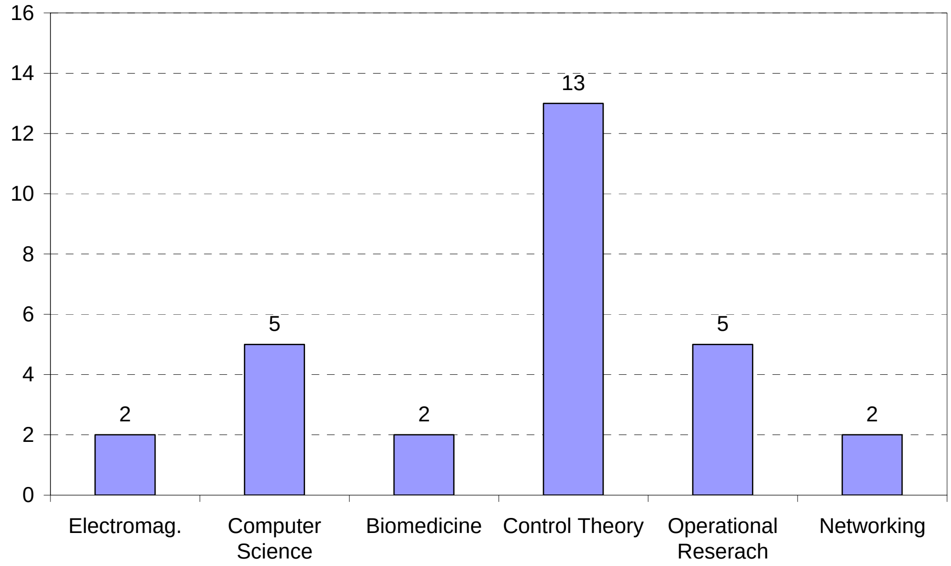

Figure 5: Fields of application of MOAIS.

Power systems

Distribution power system reconfiguration is the process of changing the topology of the distribution network by altering the open/closed status of the switches in consequence of a fault in the system. It is a complex, combinatorial optimization problem with constraints. Lin, Chen, Wu & Kang (2003) formulate the problem with two objectives 1) power losses, 2) transformer load balancing, while voltage deviation is considered as constraint. Objectives are normalized by referring them to their minimum and maximum value (obtained by a preliminary optimization phase), then a minmax approach is adopted. A Pareto-based multiobjective formulation is proposed in (Ahuja, Das & Pahwa 2007), transforming voltage deviation in the third objective.

Xiong & Cheng (2006), Xiong, Cheng, Zhang, Xu & Jia (2006) and Huang, Hsiao, Chen & Chang (2006) deal with the problem of compensating the reactive power in distribution networks.

By a proper encoding/decoding, specific generation of antibodies, and a new affinity definition, in (Xiong & Cheng, 2006) the multiobjective optimal power flow with 1) minimization of power losses and 2) maximization of voltage stability margin is solved by MOIA. The same approach is adopted in (Xiong, Cheng, Zhang, Xu & Jia, 2006) for choosing the optimal compensatory sites. Huang, Hsiao, Chen & Chang (2006) make use of fuzzy logic to normalize four objectives: 1) minimization of total costs of capacitors, 2) minimization of power losses, 3) minimization of voltage deviations and 4) maximization of system security margin of transformers.

Then a two stage procedure is applied: firstly four single objective problems are solved, by optimizing with respect to one objective and converting the others into constraints. These optimal values are used to define the utopia point for a goal programming-based AIS optimization.

The reference (Liu, Ma, Liu & Lan, 2006), faces the problem of environmental/economic dispatch, defined as the scheduling of the electrical power of a generating unit that match the local power demand with the minimum operating cost and emissions, satisfying some network equality and inequality constraints. The two objectives are aggregated by a weighted sum and solutions with different weights. The problem is solved by a genetic algorithm with immune diversity operator to improve its local search ability.

Electromagnetism

A benchmark problem in electromagnetism (TEAM 22) deals with the optimization of a superconducting magnetic energy storage system. The objectives are to maintain a prescribed level for the stored energy on the device and to minimize the stray field evaluated along fixed lines, while not violating the quench condition that assures the superconductivity state. Guimarães, Campelo, Saldanha, Igarashi, Takahashi &

Ramirez, (2006) approach the problem with three objectives: 1) minimize the stray field, 2) minimize the deviation from the prescribed value for the stored energy and 3) minimize the distance of the working point from the limit of the quench condition, with a better use of the superconducting material. Two problems are presented, with three and eight parameters.

In (Canova, Freschi & Tartaglia, 2007), a multiobjective combinatorial optimization algorithm is applied to the optimal sequence of parallel cables in a multi conductor three phase system. The objective function is built in order to minimize the magnetic stray field and the current unbalance of a bunch of rectilinear power cables. Encoding, mutation and suppression have been customized in order to fit the structure of the problem, that is similar to a multiobjective traveling salesman problem with nonlinear objectives.

Computer science

Most of attention in this area is devoted to the defense of the informatics system from an outsider attack. An analogy can be easily drawn from the biological immune system and the artificial one which should provide recognition for possible harmful pieces of information.

Anchor, Zydallis, Gunsch & Lamont (2002) introduce the computer defence immune system as an artificial immune system for virus and computer intrusion detection. In this work, the main concepts of AIS are used to define two objective functions: one objective is the antibody-antigen affinity (non-self detection) while another one is the antibody-antibody affinity (self detection). These objectives are then optimized by a multiobjective evolutionary program. Jackson, Grunsch, Claypoole & Lamont (2003) apply immune concepts to the problem of steganalysis, that is the recognition of hidden messages in ordinary files. Starting from a wavelet decomposition of graphic files Authors develop a computational immune system (CIS) able to distinguish between stego and clean images. Evolution of CIS classifier is driven by a genetic algorithm. Haag, Lamont, Williams & Peterson (2007b, 2007c) presents the need to bypass deterministic recognition of harmful information and propose a stochastic way of recognition based on evolutionary technique. Authors use a combination of immune inspired algorithms: REALGO (retrovirus algorithm) for its ability to escape local minima and MISA for handling multi-objective problems. Two objectives are considered: best classification and size of classifier hypervolume.

Another field of application, proposed by Zhang, Lu, Gou & Jiao (2006), is the learning issue. In this paper Authors face the problem of unsupervised feature selection. By use of fuzzy logic, this problem is treated like clustering by improving two different objectives: cluster quality and clusters number. Immune operators are clonal selection, updating of Ab archive and of forgetting pool. Results are presented on an artificial data set.

Biomedicine

In (Cutello, Narzisi & Nicosia 2005) a multiobjective version of the protein structure prediction problem is presented. This problem of predicting the native conformation of a protein given the amino acid sequence. Objectives are two potential energy functions: bonded (stretching, bending, torsion, Urey-Bradley, impropers) and non-bonded (van-der-Valls, electrostatics) atom energies. The problem has no constraints, with the exception of the variable bounds.

Li, Pu & Mastorakis (2006) introduce the principles of unwounded blood pressure measuring. It puts forward the application of MOIA to the identification of the values of the pulse wave crests.

Control theory

The paper (Guimarães, Palhares, Campelo & Igarashi, 2007) propose a multiobjective solution of the mixed $H2/H\infty$ control problem. Given a linear time invariant dynamic system subject to exogenous disturbances, the optimization procedure aims to determine the parameters of the controller that minimizes both the H2 and $H\infty$ of the closed loop matrices of the system. The problem is characterized by 1) nonlinear and multimodal search space, 2) non convexity and 3) search space with many continuous variables with large range size. It is shown that the proposed approach provides Pareto optimal solutions which dominates the ones obtained by a classical LMI approach for and systems with and without uncertainties.

Several works by Kim and colleagues (Kim & Hong, 2003; Kim, 2003a, 2004, 2005; Kim & Cho, 2004a, 2004b, 2005) addresses the optimal choice of a PID controller parameters in order to have a robust tuning of its dynamic response. Targets for settling time, rise time, overshoot, gain margin and phase margin are defined and fuzzy membership function are used to scalarize and aggregate the deviation from these values. Comparisons are provided with results obtained by a fuzzy logic based neural network. In (Kim, 2003b) and (Kim & Lee, 2004; Kim, Jo & Lee, 2004) the procedure is applied to the PID controller of a thermal power plant.

Concepts from immune network theory are employed to design autonomous navigation system of mobile robots in (Michelan & Von Zuben, 2002; Cazangi & Von Zuben, 2006). In the former work the robot must find and collect garbage, without colliding with obstacles and return to the base before it runs out of energy. Control actions of the robot are described by network nodes and correspond to antibodies, whereas antigens are the current states of the robot. In the latter work, the system must deal with simultaneous purposes of capturing targets and avoiding obstacles in unknown environment. Concepts from immune network theory are applied to create a network of classifiers, given rise to a so called connectionist autonomous navigation system. Both the elementary behaviours (classifiers) and their coordination dynamics (immune network) are evolved during the robot navigation. The evolutionary steps take place independently and does not require any a priori knowledge. The connectionist autonomous navigation system is shown to be capable of escaping from local minima, created by some configurations of obstacles and targets, while pure reactive navigation systems are not able to deal properly with such hampering scenarios.

Operations research

Flow shop scheduling problems addresses the determination of sequencing a number of jobs that have to be processed on a number of machines so that performance measures, e.g. makespan, tardiness, etc. are optimized.

Mori, Kitamura & Shindo (2004) propose a simulation-based scheduling method to solve the scheduling of a semiconductor test facility in presence of multiple objectives as minimization of energy consumption, makespan and tardiness and subject to different technical constraints typical of a testing process. A non automatic investigation of the nondominated solutions produced, allows the choice of the best alternatives among them. Qualitative (not quantitative) results are provided.

Extensive tests with small-sized and large sized flow shop scheduling problem problems (up to 500 jobs and 20 machines) are conduced in (Tavakkoli-Moghaddam, Rahimi-Vahed & Mirzae, 2007a, 2007b) The paper deal with a bi-criteria, where weighted mean completion time and weighted mean tardiness are minimized. Because more than one workpiece must be produced in practical production, the work of Zhou, Li, Yang, & Wang (2006) consider batch during scheduling. After having provided a methodology for deciding the starting time of jobs on machines under different move ways, an illustrative example of multiobjective batch job shop problem is solved by a MOAIS.

In (Chan, Swarnkar, & Tiwari, 2005) the problem of machine tool operation allocation of a flexible manufacturing system having as objectives 1) total machine cost, 2) total set-up cost and 3) total material handling cost and many constraints which take into account magazine capacity, tool life and machine capacity. The problem is formulated with binary variable and it is solved by a single objective AIS algorithm where objectives are fuzzyfied and constraints are incorporated into the aggregated fitness function by penalty functions.

Networking

Stevens, Natarajan & Das, (2004) propose to design of spreading codes for a DS-CDMA with a MOAIS algorithm. The problem requires to generate complex spreading codes with a wide range of auto as well as cross-correlation properties. Three ad-hoc hypermutation operators are designed to provide a faster convergence to better solutions. Results are drastically better than those produced by standard NSGA-II. Authors theorize that this is partly because the crossover operator is not well suited for the production of solutions with high cross correlation, and additionally because of the application of specific operators.

Multicast routing is an effective way to communicate among multiple hosts in a network, with several Quality of Service indicators. In (Wang, Qin & Kang, 2006) paper end-to-end delay, cost of multicast tree, and minimum bandwidth utilization are chosen as objectives (differently from previous works where single objective optimization is adopted, considering other objective as bounded constraints). To obtain solutions available for real time application, a gene library is introduced to produce better quality initial paths, rather than starting from a random population.

Analogies

Are considered as analogy papers those works which do not directly deal with MOAIS, but make reference to AIS because of some similarities with other metaheuristics.

Ahmed, & Elettreby, (2006) propose an analogy between extremal optimization and the way the immune system renews its cells. If B cells are able to recognize antigens then they are preserved

for longer period. Otherwise they are replaced randomly. This dynamics is called extremal dynamics and it can explain the long range memory of the immune system even without the persistence of antigens. The reason is that if a system evolves according to such dynamics then the annihilation probability for a clone (a type of cells) that has already survived for time t is inversely proportional to t.

Efatmaneshnik, & Reidsema, (2007) give a description of complex systems based on the analogy of immunity where the environment of a system or nonself represents the set of input and outputs with the self of the system as the resulting effect. A multiobjective approach is then adopted to find a globally robust design of a system as characteristic of the system’s self and not its environment.

FUTURE AND EMERGING TRENDS

From the analysis of the reviewed literature, it is possible to draw some considerations on MOAIS algorithms. AIS have some intrinsic characteristics which make them well suited as multiobjective optimization algorithms. Following this basic idea, different implementations have been proposed in the literature. One key point is the inherently ability to maintain population diversity, ensuring a good exploration of the search space. In other bio-inspired algorithms this feature must be enforced with proper strategies (e.g. niching and fitness sharing). This characteristic is particularly desired in multiobjective optimization, when multiple optimal solutions have to be found simultaneously. The more recent implementations of MOAIS algorithms has also the capability of automatically adapting the size of the population at each iteration, according to the demand of the application. The comparisons performed versus other metaphors seems to put forward that this can be a key point for real world, computationally expensive optimizations. Finally the memory mechanism, naturally presented by the immune system (the so called vaccine effect), is deeply exploited in multiobjective optimization to preserve optimal solutions, once they are located. It has been also theoretically proved that the presence of a memory set guarantees the elitism of the algorithm and the convergence to the optimal solutions. The dynamicity of the immune system, which is able to cope with always changing intruders, is a particularly desired characteristic in multiobjective optimization. In these problems the fitness landscape is based on Pareto dominance, thus it have to be recomputed at each time the population involved in the optimization process changes.

Despite these qualitative considerations, comparisons carried out versus other algorithms have proved neither AIS outperformances nor they inferiority for any class of problems. This last consideration open the research trends to study if there is a class of problems which is well suited to be solved by immune inspired algorithms. Our opinion is that dynamic multiobjective problems could take advantage of the peculiar characteristics of MOAIS algorithms.

From the application point of view, it seems that the progresses obtained in MOAIS algorithm have not yet exploited, with the exception of a few cases. It could be fruitful to bridge the gap between theory and algorithms and the applicative fields, by using state of the art MOAIS algorithms to solve real world application in a more effective way.

KEY TERMS AND DEFINITIONS

The definitions of the roles played by each immune concept in the optimization is provided in the following.

Antibody
Antibodies are the candidate solutions of the problem to be optimized.

Antigen
In optimization problems, antigens are the optimal configurations of the problem.

Antibody-antibody affinity
Affinity among antibodies is defined as a measure of the distance among candidate solutions. In accordance with the antibody representation, it is possible to define different distances (e.g. Euclidean for continuous representation, Hamming for binary representation, etc.), both in variable and in objective spaces.

Antibody-Antigen affinity
Scalar index adopted as measure for the goodness of a solution with respect to the objective to be optimized. It is usually related to the objective value to be minimized/maximized, with or without the use of scaling or correcting factors. In multiobjective optimization this index (also referred to as avidity) is usually obtained by ranking solutions in accordance to Pareto optimality conditions.

Avidity
see Antibody-Antigen affinity.

Memory
Memory is an offline repertoire of optimal solutions found during the evolution of the algorithm. Memory has a key role for proof of convergence of a multiobjective algorithm because it ensures the survival of the best configurations (elitism).

Suppression
In order to preserve diversity in the solutions at each iteration, antibodies which are very affine to each other (see antibody-antibody affinity) are deleted and eventually randomly replaced. Suppression can be applied either to online population or to offline memory.

BIBLIOGRAPHY

Ahmed, E., & Elettreby, M. F. (2006). On combinatorial optimization motivated by biology, *Applied Mathematics and Computation*, 172(1), 40-48.

Ahuja, A., Das, S., & Pahwa, A. (2007). An AIS-ACO hybrid approach for multi-objective distribution system reconfiguration. *IEEE Transactions on Power Systems*, 22(3), 1101-1111.

Anchor, K. P., Zydallis, J. B., Gunsch, G. H., & Lamont, G. B. (2002). Extending the Computer Defense Immune System: Network Intrusion Detection with a Multiobjective Evolutionary Programming Approach. In J. Timmis, & P.J. Bentley (Ed.) *1st International Conference on Artificial Immune Systems* (pp. 12-21).

Balicki, J. (2005). Immune systems in multi-criterion evolutionary algorithm for task assignments in distributed computer system. In *3rd International Atlantic Web Intelligence Conference* (pp. 51-56).

Balicki, J. (2004). Multi-criterion Evolutionary Algorithm with Model of the Immune System to Handle Constraints for Task Assignments. In L. Rutkowski, J.H. Siekmann, R. Tadeusiewicz, & L.A. Zadeh (Ed.), *7th International Conference on Artificial Intelligence and Soft Computing* (pp. 394-399).

Balicki, J., & Kitowski, Z. (2003). Model of the Immune System to Handle Constraints in Evolutionary Algorithm for Pareto Task Assignments. In M.A. Klopotek, S.T. Wierzchon, & K. Trojanowski (Ed.), *International Intelligent Information Processing and Web Mining* (pp. 3-12).

Campelo, F., Guimarães, F. G., & Igarashi, H. (2007). Overview of artificial immune systems for multi-objective optimization. In *4th International Conference on Evolutionary Multi-Criterion Optimization* (pp. 937-951).

Campelo, F., Guimarães, F. G., Saldanha, R. R., Igarashi, H., Noguchi, S., Lowther, D. A., & Ramirez, J. A. (2004). A novel multiobjective immune algorithm using nondominated sorting. In *11th International IGTE Symposium on Numerical Field Calculation in Electrical Engineering*.

Canova, A., Freschi, F., & Tartaglia, M. (2007). Multiobjective optimization of parallel cable layout. *IEEE Transactions on Magnetics,* 43(10), 3914-3920.

Cazangi, R. R., & Von Zuben, F. J. (2006). Immune Learning Classifier Networks: Evolving Nodes and Connections. In *IEEE Congress on Evolutionary Computation* (pp. 7994-8001).

Chan, F. T. S., Swarnkar, R., & Tiwari, M. K. (2005). Fuzzy goal-programming model with an artificial immune system (AIS) approach for a machine tool selection and operation allocation problem in a flexible manufacturing system. *International Journal of Production Research,* 43(19), 4147-4163.

Chen, J., & Mahfouf, M. (2006). A population adaptive based immune algorithm for solving multi-objective optimization problems. In *5th International Conference on Artificial Immune Systems* (pp. 280-293).

Choi, B. K., & Yang, B. S. (2001). Multiobjective optimum design of rotor-bearing systems with dynamic constraints using immune-genetic algorithm. *Journal of Engineering for Gas Turbines and Power,* 123(1), 78-81.

Chueh, C. H. (2004). *An Immune Algorithm for Engineering Optimization*. Unpublished doctoral dissertation, Department of Mechanical Engineering, Tatung University, Taipei, Taiwan.

Coelho, G. P., & Von Zuben, F. J. (2006). omni-aiNet: an immune-inspired approach for omni optimization. In *5th International Conference on Artificial Immune Systems* (pp. 294-308).

Coello Coello, C. A., & Cruz Cortés, N. (2005). Solving multiobjective optimization problems using an artificial immune system. *Genetic Programming and Evolvable Machines,* 6(2), 163-190.

Coello Coello, C. A., & Cruz Cortés, N. (2002). An Approach to Solve Multiobjective Optimization Problems Based on an Artificial Immune System. In J. Timmis, & P.J. Bentley (Ed.), *1st International Conference on Artificial Immune Systems* (pp. 212-221).

Cruz Cortés, N., & Coello Coello, C. (2003a). Multiobjective Optimization Using Ideas from the Clonal Selection Principle. In. E. Cantú-Paz (Ed.), *Genetic and Evolutionary Computation* (pp. 158-170).

Cruz Cortés, N., & Coello Coello, C. A. (2003b). Using Artificial Immune Systems to Solve Optimization Problems. In A. Barry (Ed.), *Workshop Program of Genetic and Evolutionary Computation Conference* (pp. 312-315).

Cui, X., Li, M., & Fang, T. (2001). Study of population diversity of multiobjective evolutionary algorithm based on immune and entropy principles. In *IEEE Conference on Evolutionary Computation* (pp. 1316-1321).

Cutello, V., Narzisi, G., & Nicosia, G. (2005). A class of Pareto Archived Evolution Strategy algorithms using immune inspired operators for Ab-Initio Protein Structure Prediction. In F Rothlauf (Ed.), *EvoWorkshops* (pp. 54-63).

Darmoul, S., Pierreval, H., & Gabouj, S. H. (2006). Scheduling using artificial immune system metaphors: a review. In *International Conference on Service Systems and Service Management* (pp. 1150-1155).

Das, S., Natarajan, B., Stevens, D., & Koduru, P. (2008). Multi-objective and constrained optimization for DS-CDMA code design based on the clonal selection principle. *Applied Soft Computing Journal,* 8(1), 788-797.

Efatmaneshnik, M., & Reidsema, C. (2007). Immunity as a design decision making paradigm for complex systems: A robustness approach. *Cybernetics and Systems,* 38(8), 759-780.

Freschi, F. (2006). *Multi-Objective Artificial Immune Systems for Optimization in Electrical Engineering*. Unpublished doctoral dissertation, Department of Electrical Engineering, Politecnico di Torino, Torino, Italy.

Freschi, F., & Repetto, M. (2006). VIS: an artificial immune network for multi-objective optimization.

Engineering Optimization, 38(8), 975-996.
Freschi, F., & Repetto, M. (2005). Multiobjective optimization by a modified artificial immune system algorithm, In *4th International Conference on Artificial Immune Systems* (pp. 248-261).
Guimarães, F. G., Campelo, F., Saldanha, R. R., Igarashi, H., Takahashi, R. H. C., & Ramirez, J. A. (2006). A multiobjective proposal for the TEAM benchmark problem 22. *IEEE Transactions on Magnetics*, 42(4), 1471-1474.
Guimarães, F. G., Palhares, R. M., Campelo, F., & Igarashi, H. (2007). Design of mixed H_2/H_∞ control systems using algorithms inspired by the immune system. *Information Sciences*, 177(29), 4368-4386
Haag, C. R. (2007a). *An Artificial Immune System-inspired Multiobjective Evolutionary Algorithm with Application to the Detection of Distributed Computer Network Intrusions.* Unpublished master's thesis, Department of Electrical and Computer Engineering, Graduate School of Engineering and Management, Air Force Institute of Technology, Dayton, Ohio, USA.
Haag, C. R., Lamont, G. B., Williams, P. D., & Peterson, G. L. (2007b). An artificial immune system-inspired multiobjective evolutionary algorithm with application to the detection of distributed computer network intrusions. In *6th International Conference on Artificial Immune Systems* (pp. 420-435).
Haag, C. R., Lamont, G. B., Williams, P. D., & Peterson, G. L. (2007c). An artificial immune system-inspired multiobjective evolutionary algorithm with application to the detection of distributed computer network intrusions, *In Genetic and Evolutionary Computation Conference* (pp. 2717-2724).
Huang, T. Y., Hsiao, Y. T., Chen, C. P., & Chang, C. H. (2006). Fuzzy modeling with immune multi-objective algorithm to optimal allocate of capacitors in distribution systems. *In 9th Joint Conference on Information Sciences* (pp. 289-292).
Jackson, J. T., Grunsch, G. H., Claypoole, R. L., & Lamont, G. B. (2003). Blind Steganography Detection Using a Computational Immune System: A Work in Progress. *International Journal of Digital Evidence,* 4(1), 1-19.
Jiao, L., Gong, M., Shang, R., Du, H., & Lu, B. (2005). Clonal selection with immune dominance and anergy based multiobjective optimization. In *3rd International Conference on Evolutionary Multi-Criterion Optimization* (pp. 474-489).
Kim, D. H. (2005). Tuning of PID controller for dead time process using immune based multiobjective. In *IEEE Mid-Summer Workshop on Soft Computing in Industrial Applications* (pp. 63-68).
Kim, D. H. (2004). Robust PID control using gain/phase margin and advanced immune algorithm. *WSEAS Transactions on Systems,* 3(9), 2841-2851.
Kim, D. H. (2003a). Tuning of PID controller of dead time process using immune based on multiobjective. In *7th IASTED International Conference on Artificial Intelligence and Soft Computing* (pp. 368-373).
Kim, D. H. (2003b). Intelligent 2-DOF PID control for thermal power plant using immune based multiobjective. In *IASTED International Conference on Neural Networks and Computational Intelligence* (pp. 215-220).
Kim, D. H., & Cho, J. H. (2005). Robust control of power plant using immune algorithm. In *2nd IASTED International Multi-Conference on Automation, Control, and Information Technology* (pp. 105-110).
Kim, D. H., & Cho, J. H. (2004a). Robust PID controller tuning using multiobjective optimization based on clonal selection of immune algorithm. In *8th International Conference on Knowledge-Based Intelligent Information and Engineering Systems* (pp. 50-56).
Kim, D. H., & Cho, J. H. (2004b). Robust tuning for disturbance rejection of PID controller using evolutionary algorithm. In *Annual Conference of the North American Fuzzy Information Processing Society* (pp. 248-253).
Kim, D. H., & Hong, W. P. (2003). Tuning of PID controller of dead time process using immune based on multiobjective. In *IASTED International Conference on Neural Networks and Computational Intelligence* (pp. 221-226).
Kim, D. H., Jo, J. H., & Lee, H. (2004). Robust power plant control using clonal selection of immune algorithm based multiobjective. In *4th International Conference on Hybrid Intelligent Systems* (pp. 450-455).
Kim, D. H., & Lee, H. (2004). Intelligent control of nonlinear power plant using immune algorithm based multiobjective optimization. In *IEEE International Conference on Networking, Sensing and Control* (pp. 1388-1393).
Kurapati, A., & Azarm, S. (2000). Immune network simulation with multiobjective genetic algorithms for multidisciplinary design optimization, *Engineering Optimization*, 33(2), 245-260.
Li, X., Pu, Q., & Mastorakis, N. (2006). The immune algorithm and its application to blood pressure

measuring. *WSEAS Transactions on Electronics*, 3(5), 288-292.
Li, Y., & Jiao, L. (2007). Quantum-inspired immune clonal multiobjective optimization algorithm. In *11th Pacific-Asia Conference on Advances in Knowledge Discovery and Data Mining* (pp. 672-679).
Lin, C. H., Chen, C. S., Wu, C. J., & Kang, M. S. (2003). Application of immune algorithm to optimal switching operation for distribution-loss minimisation and loading balance. *IEE Proceedings: Generation, Transmission and Distribution*, 150(2), 183-189.
Liu, H., Ma, Z., Liu, S., & Lan, H. (2006). A new solution to economic emission load dispatch using immune genetic algorithm. In *IEEE Conference on Cybernetics and Intelligent Systems* (pp. 1-6).
Lu, B., Jiao, L., Du, H., & Gong, M. (2005). IFMOA: immune forgetting multiobjective optimization algorithm. In *1st International Conference on Advances in Natural Computation* (pp. 399-408).
Luh, G., Chueh, C., & Liu, W. (2003). MOIA: Multi-Objective Immune Algorithm. *Engineering Optimization*, 35(2), 143-164.
Luh, G. C., & Chueh, C. H. (2004). Multi-objective optimal design of truss structure with immune algorithm. *Computers and Structures*, 82(11-12), 829-844.
Ma, W., Jiao, L., Gong, M., & Liu, F. (2005). An novel artificial immune systems multi-objective optimization algorithm for 0/1 knapsack problems. In *International Conference on Computational Intelligence and Security* (pp. 793-798).
Meng, H., & Liu, S. (2003). ISPEA: improvement for the strength Pareto evolutionary algorithm for multiobjective optimization with immunity. In *5th International Conference on Computational Intelligence and Multimedia Applications* (pp. 368-372).
Meng, H., Zhang, X., & Liu, S. (2005). Intelligent multiobjective particle swarm optimization based on AER model. In *12th Portuguese Conference on Artificial Intelligence* (pp. 178-189).
Michelan, R., & Von Zuben, F. J. (2002). Decentralized control system for autonomous navigation based on an evolved artificial immune network. In *Congress on Evolutionary Computation* (pp. 1021-1026).
Mori, K., Kitamura, S., & Shindo, S. (2004). Simulation-based scheduling system for saving energy consumptions. In *SICE Annual Conference* (pp. 657-660).
Shang, R., Jiao, L., Gong, M., & Lu, B. (2005). Clonal selection algorithm for dynamic multiobjective optimization. In *International Conference on Computational Intelligence and Security* (pp. 846-851).
Shang, R., & Ma, W. (2006). Immune clonal MO algorithm for ZDT problems. In *2nd International Conference on Advances in Natural Computation* (pp. 100-109).
Shang, R., Ma, W., & Zhang, W. (2006). Immune clonal MO algorithm for 0/1 knapsack problems. In *2nd International Conference on Advances in Natural Computation* (pp. 870-878).
Stevens, D., Natarajan, B., & Das, S. (2004). Multiobjective artificial immune systems based complex spreading code sets for DS-CDMA. In *4th IASTED International Multi-Conference on Wireless and Optical Communications* (pp. 364-368).
Tan, G. X., & Mao, Z. Y. (2005). Study on Pareto front of multi-objective optimization using immune algorithm. In *International Conference on Machine Learning and Cybernetics* (pp. 2923-2928).
Tan, K. C., Goh, C. K., Mamun, A. A., & Ei, E. Z. (2008). An evolutionary artificial immune system for multi-objective optimization. *European Journal of Operational Research*, 187(2), 371-392.
Tavakkoli-Moghaddam, R., Rahimi-Vahed, A., & Mirzaei, A. H. (2007a). Solving a bi-criteria permutation flow shop problem using immune algorithm. In *IEEE Symposium on Computational Intelligence in Scheduling* (pp. 49-56).
Tavakkoli-Moghaddam, R., Rahimi-Vahed, A., & Mirzaei, A. H. (2007b). A hybrid multi-objective immune algorithm for a flow shop scheduling problem with bi-objectives: Weighted mean completion time and weighted mean tardiness. *Information Sciences*, 177(22), 5072-5090.
Villalobos-Arias, M., Coello Coello, C. A., & Hernández-Lerma, O. (2005). Asymptotic convergence of some metaheuristics used for multiobjective optimization. In *Revised Selected Papers of 8th International Workshop on Foundations of Genetic Algorithms* (pp. 95-111).
Villalobos-Arias, M., Coello Coello, C. A., & Hernández-Lerma, O. (2004). Convergence analysis of a multiobjective artificial immune system algorithm. In *3rd International Conference on Artificial Immune Systems* (pp. 226-235).
Wang, J. Q., Qin, J., & Kang, L. S. (2006). A new QoS multicast routing model and its immune optimization algorithm. in *3rd International Conference on Ubiquitous Intelligence and Computing* (pp. 369-378).
Wang, X. L., & Mahfouf, M. (2006). ACSAMO: An Adaptive Multiobjective Optimization Algorithm using the Clonal Selection Principle. In *2nd European Symposium on Nature-Inspired Smart Information Systems* (pp. 1-12).

Xiong, H. and Cheng, H. (2006). Multi-objective optimal reactive power flow incorporating voltage stability. *WSEAS Transactions on Power Systems*, 1(3), 613-618.

Xiong, H., Cheng, H., Zhang, W., Xu, Y., & Jia, D. (2006). Optimal reactive power compensation planning with improving voltage stability margin in deregulated environment. *WSEAS Transactions on Circuits and Systems*, 5(1), 104-110.

Yoo, J., & Hajela, P. (2001). Fuzzy Multicriterion Design Using Immune Network Simulation. *Structural and Multidisciplinary Optimization*, 22(3), 188-197.

Yoo, J., & Hajela, P. (1999). Immune network simulations in multicriterion design. *Structural Optimization,* 18, 85-94.

Zhang, X., Lu, B., Gou, S., & Jiao, L. (2006). Immune multiobjective optimization algorithm for unsupervised feature selection. In *10th Pacific-Asia Conference on Advances in Knowledge Discovery and Data Mining* (pp. 484-494).

Zhang, X., Meng, H., & Jiao, L. (2005a). Improving PSO-based multiobjective optimization using competition and immunity clonal. In *International Conference on Computational Intelligence and Security* (pp. 839-845).

Zhang, X., Meng, H., & Jiao, L. (2005b). Intelligent particle swarm optimization in multiobjective optimization. In *IEEE Congress on Evolutionary Computation* (pp. 714-719).

Zhang, Z. (2007). Immune optimization algorithm for constrained nonlinear multiobjective optimization problems. *Applied Soft Computing Journal*, 7(3), 840-857.

Zhang, Z. (2006). Constrained Multiobjective Optimization Immune Algorithm: Convergence and Application. *Computers and Mathematics with Applications,* 52(5), 791-808.

Zhou, Y., Li, B., Yang, J., & Wang, Q. (2006). An immune algorithm for batch job-shop scheduling with multi-objectives. In *International Technology and Innovation Conference* (pp. 1642-1646).

FURTHER READING

Coello Coello, C. A.; Van Veldhuizen, D. A., & Lamont, G. B. (2007). *Evolutionary Algorithms for Solving Multi-Objective Problems*. 2nd ed, New York, USA: Springer-Verlag.

Collette, Y., & Siarry, P. (2003). *Multiobjective Optimization. Principles and Case Studies*. Springer-Verlag.

de Castro, L., & Timmis, J. (2002). *Artificial Immune Systems: A New Computational Intelligence Approach.* London, UK: Springer-Verlag.

Deb, K. (2001). *Multi-Objective Optimization Using Evolutionary Algorithms*. John Wiley, & Sons, Chichester, UK

Forrest, S., & Perelson, A.S. (1991). Genetic algorithms and the immune system. In *Parallel Problem Solving From Nature*, (pp. 320-325), Berlin, Germany: Springer-Verlag.

Miettinen, K. (1999). *Nonlinear Multiobjective Optimization*. Boston, Massachusetts, USA: Kluwer Academic Publishers.

Pareto, V. (1896). *Cours d’Economie Politique*, Vol. I-II , Lausanne, Switzerland: F. Rouge.