A Clonal Selection Algorithm for Optimization in Electromagnetics

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This paper proposes the real-coded clonal selection algorithm (RCSA) for use in electromagnetic design optimization. Some features of the algorithm, such as the number of clones, mutation range, and the fraction of the population selected each generation are discussed. The TEAM Workshop problem 22 is investigated, in order to illustrate the performance of the algorithm in a real electromagnetic problem. The results obtained, a set of optimal solutions representing a broader range of options for the designer, are compared with those achieved by a genetic algorithm, showing the efficiency of the RCSA in practical optimization problems.

Index Terms—Artificial immune systems, electromagnetic design optimization.

I. INTRODUCTION

The area of artificial immune systems (AIS) has been experiencing an increasing development in the last few years, with applications in pattern recognition, network security, and optimization, amongst other fields of research. There are some works in which new algorithms are presented, discussed, and tested against analytical problems, showing very promising results [1]. However, there are few using immune algorithms for electromagnetic design optimization [2], [3]. In the latter, the algorithms presented use binary coding of the individuals and require a large number of objective function evaluations for finding the optimum, two undesirable characteristics when optimizing electromagnetic devices.

One of the models used to explain the behavior of the immune system is the clonal selection principle. A very clear overview of this principle, from immunology and engineering points of view, is presented in [4]. In the same work, the authors proposed an algorithm for performing pattern recognition and multimodal optimization. The clonal selection algorithm (CSA) is a population-based stochastic method, with binary representation of the variables. CSA is capable of optimizing multimodal functions and maintaining local solutions, two valuable characteristics for electromagnetic design optimization.

However, since most of the optimization problems in electromagnetics use real-valued variables, a real-coded algorithm arises as an interesting option. With this in hand, one can work directly with the variable values, skipping coding-decoding steps and making the algorithm simpler. Moreover, some modifications in the algorithm structure and operators can be made, in order to achieve better performance and reduce the number of objective function evaluations needed.

In this work, we propose a new implementation for the CSA, called the real-coded clonal selection algorithm (RCSA) for numerical electromagnetic problems. Although this algorithm is based on the CSA, some modifications have been proposed in order to make it more suitable for optimization in electromagnetics. The structure, parameters and operators of the algorithm are described, and a sensitivity analysis of the RCSA is presented. The algorithm is tested with analytical functions and in an electromagnetic problem. The results are compared with those obtained with the best genetic algorithm discussed in [5].

II. RCSA

Suppose the general unconstrained optimization problem

\[ \max f(\vec{x}) \in \mathbb{R} \]

\[ \vec{x}_- \leq \vec{x} \leq \vec{x}_+ \]  

(1)

where \( \vec{x} \in \mathbb{R}^n \) is the variable vector, \( f(\cdot) : \mathbb{R}^n \rightarrow \mathbb{R} \) is the objective function and \( \vec{x}_-, \vec{x}_+ \) are the limits of the search space (box constraints).

The RCSA starts with the generation of an initial population, usually by spreading \( n_{\text{pop}} \) random points in the search space. These points are evaluated over an affinity (fitness) function, which can be the objective function \( f(\vec{x}) \) in the case of maximization problems, or \( -f(\vec{x}) \), in the case of minimization functions, and ranked in decreasing order of affinity. The first \( \eta \% \) points are then selected for cloning. Each of these individuals receive a number of copies proportional to its position in the ranking, given by

\[ N_{\mathcal{C}} = \text{round} \left( \frac{\vec{x} \cdot n_{\text{pop}}}{i} \right) \]  

(2)

The clones, not the original individual, then undergo the maturation (hypermutation) process: Each clone is submitted to Gaussian noise on at least one variable. The standard deviation of the noise for a given variable \( x_j \) is a fraction of the size of the search space for that variable \( S(x_j) \), as follows:

\[ x_j = x_j(1 + p \cdot S(x_j) \cdot \text{Gauss}(0,1)) \]  

(3)

where \( p \) is a small number; in this work, we used 0.1, and \( \text{Gauss}(0,1) \) is a random Gaussian variable with zero mean.

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and unitary standard deviation. The use of Gaussian mutation allows the exploration of the vicinity of the original individual and maintains the possibility of medium-range exploration of the search space. A given individual and its maturated clones forms a subpopulation of points in the search space.

The maturated clones are evaluated over the affinity function, and the best of each subpopulation is allowed to pass to the next generation, in a process much alike the global elitism [6]. In genetic algorithms, this kind of elitism tends to reduce the population diversity, but RCSA avoids it by replacing the individuals not selected for cloning in a given generation by new random points. With this replacement, the diversity is maintained and new areas of the search space can be potentially explored.

The basic structure of the RCSA is described in Appendix I. This algorithm incorporates new characteristics in comparison to previous works [2], [3].

III. SENSITIVITY ANALYSIS

As seen in the previous section, the RCSA has only four main parameters for adjusting: the size of the population, npop; the maximum number of generations, maxgen; the rate of the population selected for cloning, n; and the multiplying factor for cloning, β. In this section, we study the effect of these parameters on the performance of the algorithm over a sample test function. For evaluating the sensitivity of the algorithm to its parameters, we used the following methodology: the algorithm was ran 200 times over a test function, each parameter was varied over a wide range whilst the other parameters were kept constant. The range of the variation and the base value for each parameter are shown in Table I. The base values were selected in order to achieve an approximate 80% convergence in the maximization of the test function

\[ f(\mathbf{x}) = 10n + \sum_{j=1}^{n} x_j^2 - 10 \cos(2\pi x_j) \]  (4)

with \( n = 4 \). This function is characterized by the existence of \( 10^9 - 1 \) local maxima in the interval \(-5.12 < x_j < 5.12\) and a global maximum at \( x_j = 0, \forall j \in 1, \ldots, n \). The convergence criterion used is \( ||\mathbf{x}||_2 < \sqrt{10} \), as suggested in [6].

As shown in Fig. 1, the convergence rate of the RCSA, over the test function, approaches 100% asymptotically as the population size is increased. The number of function evaluations increases almost linearly with the increase of the population size. Figs. 2 and 3 show that the variation of maxgen and β has a similar effect on the convergence rate and the number of function evaluations of the algorithm, i.e., the increase of maxgen and β resulted in an asymptotical increase of the convergence rate and a linear increase of the number of objective function evaluations.

The variation of the rate of the population n selected for cloning, however, had a different effect on the algorithm, see Fig. 4. The convergence rate increases up to 85% as n rises from low values up to near 0.65. This means that almost no individuals of the population are selected for cloning, making this configuration similar to a random search. Then, the value of the convergence rate falls to values smaller than 85%, to near 78%, as n approaches 1, \( 0.65 < n \leq 1 \). This means that almost no new individuals are being introduced in the population, i.e., no global exploration is being made. The number of objective function evaluations increases asymptotically to a value near 680 evaluations.

IV. RESULTS

A. Analytical Problem

Let us consider, again, the function given by (4). For the problem of maximizing the two-variable version of this function, the RCSA, with npop = 15, maxgen = 10, n = 0.6, β = 0.8, which means 384 objective function evaluations, was able
The TEAM Workshop problem 22 is a well known benchmark problem for optimization algorithms [5]-[7]. It consists in minimizing the stray field in a superconducting magnetic energy storage (SMES) device, shown in Fig. 6. The objective function is given by

\[ f(\bar{x}) = \sqrt{\frac{\sum_{i=1}^{21} |B_{S_i}|^2}{21}} \]  

(5)

where \( B_{S_i} \) is the magnetic flux density evaluated at each of the 21 points.

This problem has two constraints: An equality constraint, concerning the amount of energy stored at the SMES device

\[ h(\bar{x}) = \frac{E}{180 \times 10^6} - 1 = 0 \]  

(6)

where \( E \) is the energy stored by the SMES device and an inequality constraint, concerning the quench condition that guarantees superconductivity

\[ g(\bar{x}) = B_{\max} - 4.92 \leq 0 \]  

(7)

where \( B_{\max} \) is the highest value for the magnetic field density, which must be lower than 4.92 T. In this work, the constraints were treated using a penalty function. The penalized objective function is then given by

\[ p(\bar{x}) = f(\bar{x}) + 100(h(\bar{x})^2 + \max(g(\bar{x}),0)^2) \]  

(8)

We have investigated the three-variable version of the problem 22, in which the three variables are associated to the external coil \( (r_2, h_2, d_2) \), as defined in [8]. The three-variable ranges, as well as the constant values, are shown in Table II.

Table III shows the results obtained using the RCSA, with \( \text{pop} = 15, \text{maxgen} = 15, n = 0.6, \beta = 0.7 \). This configuration consumed 512 evaluations of the device, and was able to return eight optimum points. The results obtained are compared to [5], which consumed 2400 objective function evaluations and to the best known solution for this problem [8].

It can be seen in Table III that the best SMES configuration found by RCSA has a \( B_{\max} \) value lower than the other solutions shown, and that it respects the energy constraint, with an error...
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RCSA was also very successful in optimizing the SMES device, at an acceptable computational cost. It was able to find a solution comparable to a powerful genetic algorithm and to the best solution available in the literature, whilst not violating the constraints. These results show the feasibility of the RCSA in solving real electromagnetic optimization problems.

APPENDIX I

RCSA

Given
- maxgen—maximum number of generations
- nbpop—population size
- p—rate of the population selected for cloning
- f—multiplying factor for cloning

Do
- Create initial population;
- ∅gen = 0;
- While ∅gen < maxgen
  • evaluate individuals;
  • select the nbpop × r1 best individuals and clone it;
  • maturate the clones, and evaluate it;
  • allow the best individual from each subpopulation to survive;
  • Replace the individuals not cloned by new (random) individuals;
  - ∅gen = ∅gen + 1
- End While
- End Do

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