A Robust Metaheuristic Based on Clonal Colony Optimization and Population Based Incremental Learning Methods

S. L. Ho[1], Shiyou Yang[2], and Yanan Bai[2]

[1]Department of EE, The Hong Kong Polytechnic University, Hong Kong

[2]College of Electrical Engineering, Zhejiang University, Hangzhou, China

***Abstract*—To provide a fast robust optimizer for numerical solutions of inverse problems, a metaheuristic based on population based incremental learning and clonal colony optimization methodology is proposed. In the proposed algorithm, a real valued probability vector is introduced to extend the colony, a tournament based mechanism is employed in a colony to destruct/discard plants to evolve the colony towards promising space, and a new reallocation operator is designed. The numerical results on two case studies are reported to positively confirm the merits of the proposed metaheuristic.**

***Index Terms*—Evolutionary computation, inverse problem, robustness.**

I. Introduction

Design optimization is a multi-disciplinary study employing scientific and technological approaches to satisfy technical, economical and social requirements in an optimal manner. Due to keen competitions, engineers nowadays are under immense pressure to produce optimal designs in order to survive. It is increasingly difficult to find optimal designs of an electromagnetic device or system using traditional approaches. In this regard, a wealth of efforts is being devoted to computational intelligence in attempts to find solutions of inverse problems or optimizations in computational electromanetics in the last three decades [1].

In practical engineering design problems, uncertainties are often inevitable. If the optimized solution is very sensitive to small variations of the optimized decision parameters, it is possible that slight perturbations in the optimized variables could result in significant performance degradation or infeasible solutions by violating the constraint functions. Hence, it is equally important to explore robust optimal techniques in studies of inverse problems under conditions of uncertainties in computational electromagnetics [2],[3].

Robustness means some degree of insensitivity to small disturbances in either the decision or environmental variables. Generally, the mean (expected fitness) and standard deviation are commonly used as the gauge to assess the robustness of objective and soft constraint functions, while the worst case philosophy is simply used for a hard constraint function in literature [4]. This means a number of additional points in the small neighborhood of a given solution are sampled and their function values are used to approximate the robust metric of the specific solutions, as there is no close-form solution for such evaluation in a real world inverse problem. In other words, the computational burden for a robust optimizer is significantly higher than that for its global counterpart. To address this issue, a metaheuristic combined population based incremental learning and clonal colony optimization algorithm is proposed to find robust solutions without incurring extra computational cost to evaluate the robust performances of candidate solutions.

II. A Robust Metaheuristic

Clonal colony optimization, inspired by the reproduction mechanics of plant clonal colonies [5], is a population based evolutionary algorithm. Briefly speaking, in the clonal colony optimization method, a population is comprised of different colonies and each colony is grouped by several plants (solutions). In the iterative process, the colonies evolve by means of destruction and extension operations [5], as schematically described in Fig.1.

```
Iterative Procedure of the proposed algorithm
Seed colonies randomly in the yard
    while(stop condition is not satisfied)
        ForEach (Colony c in the yard)
            Purge (c)
            Extend (c)
            Split (c)
        Reallocate ()
    Distill(solutions in the yard)
```

Fig. 1 The iterative procedures of the proposed algorithm

The promising salient feature of the clonal colony optimization method is that the average fitness value of the plants in a colony could be used as the robust performance parameter of the colony. However, to fully use this characteristic, the operators of the algorithm should be properly designed. In this regard, the corresponding operators are designed as follows.

Extend: To balance exploitation and exploration searches, a real valued probability vector, as used in a population based incremental learning method [6], is introduced to extend the colonies. The length of this real value probability vector is identical to that of the encoded chromosome of a feasible solution in the optimal problem. The value of each element of the vector is the probability of having a *1* in that particular bit position of the encoded chromosome. In every iterative cycle, a new plant is generated in such a way that the probability for the i^{th} bit of the chromosome of the new plant to be *1* is proportional to the value of the i^{th} element of this probability vector. In contrast to the original method, this probability vector is updated using the *elite* plant of the total ones in the same colony in the latest N_e cycles following

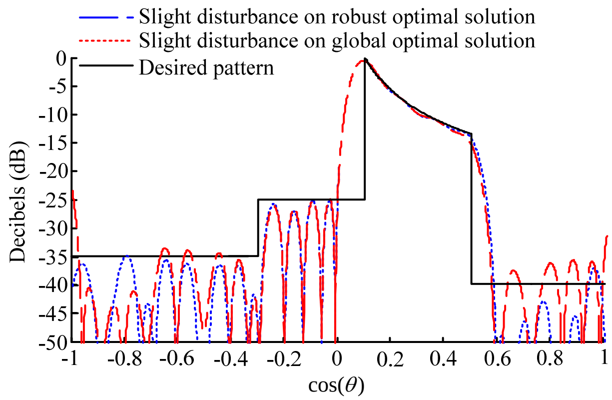

Fig.2. Field pattern degradations of the global and robust solutions.

$$p^j(i) = (1.0 - LR^j) \cdot p^j(i) + LR^j \cdot elite^j(i) \qquad (1)$$

where; LR^j is the learning rate of colony j; $elite^j(i)$ is the value of the i^{th} bit of the binary encoded string of the *elite* plant so far searched in the colony in the latest N_e cycles.

Purge: To mimic "the fittest survive" principle of nature selection, a tournament based mechanism according to the fitness value is used in a colony to destruct/discard plants to evolve the colony toward promising space.

Split: The split operator used in the proposed metaheuristic is the same as that of [5]. However, the predefined maximum distance between two plants in a colony to split it is defined as the amplitude of the possible perturbations on the corresponding decision variable.

Reallocate: After splitting, the split plants are needed to regroup to other colonies. For this purpose, the feasible parameter space is divided into a discrete grid according to a user predefined precision parameter. Once a plant is needed to split to another colony, its location in the grid is determined by repeatedly bisecting the range of it in each direction and to identify the specific half range that contains the plant. After the location is identified, the colony of the specified plant is determined.

III. Numerical Applications and Conclusions

In the case studies, the average fitness value of the plants in a colony is used as the robust performance parameter of the colony in the proposed algorithm without invoking any additional computation due to the properly designed algorithm.

A. Application One

The optimal design of a non-linear antenna array [7] is firstly solved using the proposed metaheuristic to find the robust optimal solution of the problem. In this case study, a desired field pattern of shaped beams with a cosecant variation is reconstructed using a 26-element non-uniform antenna array. In numerical implementations, small perturbations of up to 0.2% on the decision variables are assumed. After 52465 iterations, the proposed algorithm finds a robust optimal solution with the mean fitness value of 1.831620, which is compared to 58779 iterations of the combined polynomial chaos and PSO algorithm with the same final solution [8]. Also, some post-processing treatments are implemented on the robust optimal as well as the global optimal solution which is searched by using a conventional evolutionary algorithm, and it is found that the violation probabilities for the constrained conditions of the two optimal solutions with uncertainties of small variations of up to 0.2% on the decision variables are respectively, 20% and 60% for the robust and global ones. Fig. 2 depicts intuitively the field pattern degradations when the two optimal solutions are disturbed by a slight tolerance.

B. Application Two

The robust optimal counterpart of the Team Workshop problem 22 of a superconducting magnetic energy storage (SMES) configuration with three free parameters [9] is then solved using the proposed metaheuristic. In the numerical study, small variations of up to 1% on the decision variables are randomly perturbed to the decision variables. After 2541 iterations, the proposed algorithm found a robust solution and the performance parameters for the robust optimal solution are: the stray field: 7.54×10^{-7}, the stored energy: 179.3141 MJ; these are compared with, 7.73×10^{-7}, 179.91 MJ to the global optimal solution [9]; with a 1% perturbation, these performances will be 1.107×10^{-6}, 178.96 MJ for the robust optimal solution; and 1.410×10^{-6}, 183.28 MJ for the global optimal solution.

From the numerical results on the two case studies; it is obvious the robustness for the optimized solution using the proposed algorithm is significant stronger than that of those using the available optimal technique; and moreover, the increase of the iterative number used by the proposed algorithm is not significant since the proposed robust methodology incurs no extra computational cost in the evaluation of the robust performances of candidate solutions.

References

[1] David A. Lower, "Application of intelligent system technology to design optimization," *Tutorial 1 of CEFC'2000*, Milwaukee, Wisconsin, USA, 2000.

[2] G. L. Soares, R. L. S. Adriano, C. A. Maia, L. Jaulin, and J. A. Vasconcelos, "Robust multi-objective TEAM 22 problem: a case study for uncertainties in design optimization," *IEEE Trans. Magn*., vol. 45, pp. 1028-1031, Mar. 2009.

[3] Nam-Kyung Kim, Dong-Hun Kim, Dong-Wook Kim, Heung-Geun Kim, Lowther D.A., Sykulski J.K.; "Robust optimization utilizing the second-order design sensitivity information," *IEEE Trans. Magn*., vol. 46, pp. 3117 - 3120, Aug. 2010.

[4] H. G. Beyer, and B. Sendhoff, "Robust optimization-a comprehensive survey," *Comput. Methods Appl. Mech. Engrg*., vol. 196, pp. 3190-3218, 2007.

[5] Jorge Maturana, Fernando Vergara, "Robust optimization by means of vegetative reproduction," *Lecture Notes in Computer Science*, vol. 6943, pp. 404-415, 2011.

[6] Marcus Gallagher, and Marcus Frean, "Population-based continuous optimization, probabilistic modelling and mean shift," *Evolutionary Computation*, vol. 13, pp. 29-42, 2005.

[7] A. Akdagli and K. Guney, "Shaped-beam pattern synthesis of equally and unequally spaced linear antenna arrays using a modified tabu search algorithm," *Microwave Opt. Technol. Lett*., vol. 36, pp. 16-20, 2003.

[8] S. L. Ho, and Shiyou Yang, "A fast robust optimization methodology based on polynomial chaos and evolutionary algorithm for inverse problems," *IEEE Trans. Magn.*, vol. 48, pp.259-262, 2012.

[9] TEAM optimization benchmark problem 22 [online], available at: http://www.igte.tugraz.at/team22/.