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# A self-organizing migrating genetic algorithm for constrained optimization

Kusum Deep *, Dipti

*Department of Mathematics, Indian Institute of Technology Roorkee, Roorkee 247 667, India*

**Abstract**

In this paper, a self-organizing migrating genetic algorithm for constrained optimization, called C-SOMGA is presented. This algorithm is based on the features of genetic algorithm (GA) and self-organizing migrating algorithm (SOMA). The aim of this work is to use a penalty free constraint handling selection with our earlier developed algorithm SOMGA (self-organizing migrating genetic algorithm) for unconstrained optimization. C-SOMGA is not only easy to implement but can also provide feasible and better solutions in less number of function evaluations. To evaluate the robustness of the proposed algorithm, its performance is reported on a set of ten constrained test problems taken from literature. To validate our claims, it is compared with C-GA (constrained GA), C-SOMA (constrained SOMA) and previously quoted results for these problems.
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*Keywords:* Genetic algorithms; Self-organizing migrating algorithm; Self-organizing migrating genetic algorithm; Leader; Active; Path length; Step size

## 1. Introduction

A general nonlinear constrained optimization problem is formulated as follows:

$$\begin{aligned}&\text{Min}\quad f(x),\ x \equiv (x_1, x_2, \ldots x_n)\\&\text{Subject to:}\\&\qquad \left.\begin{aligned} x \in D = \{x \in \Re^n / g_k(x) \geqslant 0, &\quad k = 1, 2, \ldots K\\ h_m(x) = 0, &\quad m = 1, \ldots M\\ a_i \leqslant x_i \leqslant b_i, &\quad i = 1, 2 \ldots n\}, \end{aligned}\right\}\end{aligned} \tag{1}$$

where $f(x)$ is the objective function to be minimized, $g_k(x) \geqslant 0$ for $k = 1, 2, \ldots K$ are inequality constraints, $h_m(x) = 0$ for $m = 1, 2, \ldots M$ are equality constraints, $a_i$ and $b_i$ represent the lower and upper bounds on the decision variables.

* Corresponding author.
*E-mail addresses:* kusumfma@iitr.ernet.in (K. Deep), diptipma@rediffmail.com (Dipti).

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Many real life problems arising in science, business, engineering etc can be modeled as nonlinear constrained optimization problems. To solve these problems, population based stochastic search methods have been frequently used in literature. Some advantages of using these methods are as follows:

- They attempt to determine the global optimal solution.
- They do not use continuity/differentiability conditions of the functions involved and can work on non-differentiable functions as well.
- They do not need an initial guess value to initiate them, but work with a lower and upper bound of the unknown variables.

Though GAs are very efficient at finding the global optimal solution of unconstrained or simply constrained (i.e., box constraints) optimization problems but encounter some difficulties in solving highly constraint nonlinear optimization problems, because the operators used in GAs are not very efficient in dealing with the constraints. Several methodologies have been developed to handle constraints when GAs are used to solve constrained optimization problems refer Kim and Myung [1], Michalewicz [2], Myung and Kim [3], Orvosh and Davis [4]. These methods can be classified as follows:

(i) *Rejecting strategy*
This strategy is based on the rejection of infeasible solutions during the search process and considers only feasible solutions. The main drawback of this strategy is that if at any stage all solutions are infeasible than this strategy fails to work.

(ii) *Repairing strategy*
In this strategy, infeasible solutions are repaired to feasible solutions using some repair procedure. Though this approach is very effective in solving several constrained optimization problems but are usually problem specific and sometimes more complicated than the problem itself.

(iii) *Modifying genetic operator strategy*
In this strategy, the genetic operators are modified according to the requirement of the problem to maintain the feasibility of solutions. It is also problem specific.

(iv) *Penalty function strategy*
In this strategy, infeasible solutions are penalized using a penalty parameter. Before applying this strategy first the constrained problem is transformed to an unconstrained problem in which the function to be minimized has the following form:

$$\phi(x,r) = f(x) + r\sum_{m=1}^{M}[h_m(x)]^2 + r\sum_{k=1}^{K} G_k[g_k(x)]^2, \tag{2}$$

where $G_k$ is the Heaviside operator such that $G_k = 0$ for $g_k(x) \geqslant 0$ and $G_k = 1$ for $g_k(x) < 0$, and $r$ is a positive multiplier which controls the magnitude of penalty terms.

Among these, penalty function strategies are most commonly used and are considered to be very effective to produce feasible solutions but have some drawbacks also. Many attempts have been made in literature to improve the efficiency of these penalty parameter based approaches. Refer Homaifar et al. [5], Michalewicz and Attia [6], Joines and Hauck [7] etc. The main drawback of this approach is that penalty parameter has to be fine tuned. If this parameter is not handled properly then there are more chances of getting infeasible solutions (Coello [8], Smith and Coit [9]). Therefore, other alternative penalty free approaches have been suggested. Deb and Agarwal [10] proposed a niched-penalty approach for constraint handling in GAs which does not require any penalty parameter. Coella and Mezura-Montes [11] proposed a constraint handling approach for GAs which uses a dominance-based selection scheme. It does not require the fine tuning of a penalty function and extra mechanisms to maintain diversity in the population. Akhtar et al. [12] proposed a socio-behavioral simulation based approach to solve engineering optimization problems. They simulate societies in this approach. The main advantage of this approach is that it requires low number of function evaluations to obtain good results, but does not reach the optimum. Its main drawback is that the implementation is not easy.

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