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Review of constrained optimization problem solving using evolutionary algorithms

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ABSTRACT – A problem with constraints is difficult to be optimized due to various limits on the decision variables, the interference among constraints and the interrelationship between the constraints and the objective function. These problems are known as constrained optimization problems (COPs). Evolutionary algorithms are getting popular among researchers in solving COPs due to their simplicity, flexibility and robustness. In this work, we i) survey the variety of evolutionary algorithms used in solving real world COPs. We also ii) discuss the difficulties concerned with solving constraints, and we iii) review the constraint handling techniques applied to each COPs.

1. INTRODUCTION

The general mathematical equation for COP can be stated as [1]:

Minimize	$f(x)$	(1)
Subject to	$g_i(x) \leq 0, i = 1, 2, 3 \ldots p$	(2)
	$h_j(x) = 0, j = 1,2,3 \ldots q$	(3)
	$x \in S$	(4)

In this formulation, f is the objective function, x is an n-dimensional vector of unknowns, $x = x_1, x_2, \ldots, x_n$, g_i, $i = 1, 2, \ldots, p$, and $h_j, j = 1, 2, \ldots, q$, are real-valued constraints functions of the variables $x_1, x_2, \ldots, x_n$. The set S is a subset of n-dimensional space.

Nature-inspired Evolutionary Algorithms (EAs) are commonly used to solve COPS because of four main reasons: simplicity, flexibility, derivation-free mechanism, and local optima avoidance [2]. However, EAs were designed to deal with unconstrained search space [3].

Constraint-handling techniques (CHTs) are introduced with EAs to guide the search space. According to Koziel and Michalewicz [4] , these CHTs are categorized into four group which are (a) methods based on preserving feasibility of solutions (b) methods based on penalty functions, (c) methods based on a search for feasible solutions, (d) and hybrid methods.

This paper is organized as follows: Section 2 briefly explains about EAs and reviews their application towards benchmark test functions. Section 3 surveys EA application for real world constrained problem. Finally, section 4 summarizes all findings, suggests some directions for future research and lastly, conclude the study.

2. EVOLUTIONARY ALGORITHM

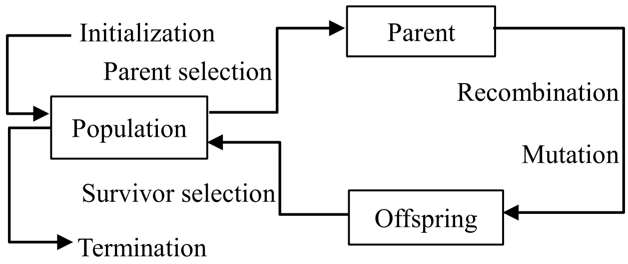

Figure 1. Evolutionary cycle

EAs use iterative progress where a set of solutions or agents are first initializes before selected agents are positively or negatively selected , in order to produce a better solution. The selection is made depending on their relative success in surviving and reproducing in the environment. Fitness of each agent is evaluated and measured by means of an objective function to be optimized, often either minimization or maximization function [5]. Figure 1 illustrates the process.

Genetic algorithm (GA) is an example of EAs. It models evolution of chromosomes. The chromosomes of GA represent candidate solutions. The space of possible solutions is searched by mimicking phenomenon that appear in the chromosomes of living organisms such as crossover, inversion, point mutation, and more so that a new and improved set of solutions are generated [6].

A lot of works had been performed on solving COP using GA. In the work by Venkatraman and Yen [7], they proposed a generic framework of using GA to solve COP. They carefully constructed an optimization model resulted from a combination of GA and two-stage non-dominated rank-based CHT to work on an objective function-constraint violation search space. This way the model simultaneously produce feasible solutions without compromising the agent exploration. They tested on updated test case generator (TCG-2) and 11 test functions from [8]. This method is proven to find feasible solutions in all runs for each problem tested including problem involving nonlinear constraints.

Recent studies by Umbakar et al [9] proposed Dual Population Genetic Algorithm (DPGA) for solving COP. The proposed CHT is called Maximum Constraints Satisfaction Method (MCSM) where firstly, Pseudo Random Number Generator (PRNG) selects variables to prepare agents which satisfy all constraints followed by second phase of MCSM, DPGA is applied for evolution of both populations via inbreeding one main population with several reserve populations. The reserve population have different fitness function where high fitness values are given for the agent which average distance between the agents to the main population is large. It is to add diversity to the agents of the main population. The limitation on this work is that the technique only work with inequality constraints. The proposed method is tested with CEC 2006 test functions.

Q. Long [10] proposed constrained multiobjective genetic algorithm (CMOGA) to be tested on CEC2009 test functions. He introduced a new rank-based CHT called optimal sequence method (OSM) which rank those agents who are more reasonable based on their feasibility, diversity and elitism metric, in the foremost positions rather than Pareto solutions. It distinguishes OSM from Pareto ranking. However, it is also mentioned that this method only works for small and medium size problem.

3. SOLVING REAL WORLD CONSTRAINED OPTIMIZATION PROBLEMS

There are many COPs in real world optimization problem. An example of such problem is aircraft landing problem (ALP). ALP is the problem of sequencing a fleet of incoming aircraft subject to the available runway, fuel and various other constraint. In the work of Y. Guo et al [11], they introduced multi objective EA (MOEA) to solve ALS. MOEA is combined with CHT developed based on Deb's rule [12]. The algorithm is tested with previous case study from [13].

D. Munk et al [14] discuss the use of Bi-directional Evolutionary Structural Optimisation (BESO) in solving a design challenge of an L-shaped clamped beam with a roller support at the top of the vertical-tie, also known as Zhou-Rozvany (Z-R) problem. The algorithm manage to increase the accuracy of sensitivity criterion and reduce computational time. A connectivity filter as CHT is introduced to maintain feasibility before achieving high optimality solution.

R. Moeini et al [15] introduced gravitational search algorithm (GSA) for simple and hydropower operation of a single reservoir. The problem is to minimize water releases within a duration of operation subject to water storage and other constraints. They handle the constraints by modifying the storage volume bounds of the reservoir prior to the main search. It means only feasible agents available in the search space. However, this method only works for single reservoir problem hence it needs to be modified for multi-reservoir problem.

4. CONCLUSION

A number of EAs application in solving COP is reviewed throughout this study. Finally, examples for real world COPs and the application of EAs to solve these problems are discussed in this paper.

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