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An efficient biogeography based optimization algorithm for solving reliability optimization problems

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ABSTRACT

The objective of this paper is to solve the reliability redundancy allocation problems of series–parallel system under the various nonlinear resource constraints using the penalty guided based biogeography based optimization. In this type of problem both the number of redundant components and the corresponding component reliability in each subsystem are to be decided simultaneously so as to maximize the reliability of the system. A parameter-free penalty function has been taken which encourages the algorithm to explore within the feasible region and the near feasible region, and discourage the infeasible solutions. Four benchmark problems with the reliability, redundancy allocation problems are taken to demonstrate the approach and it has been shown by comparison that the solutions by the approach are better than that of solutions available in the literature. Finally statistical simulation has been performed for supremacy the approach.

1. Introduction

The system reliability optimization is very important in the real world applications and the various kinds of systems have been studied in the literature for the decades. Generally there are four ways to design the highly reliable system by improving the system reliability. These are (a) increasing the component reliability, (b) using redundant components in parallel, (c) a combination of component reliability enhancement and using the redundant component in parallel; and (d) reassignment of interchangeable components. But increasing the component reliability alone will usually increase the system resources (cost, weight, volume, etc.) and hence it is important for the system analyst or plant personnel maintain these resources so to get the balance between reliability and other resources. Therefore, the combination of the component reliability enhancement and using the redundant component in the parallel reassignment of interchangeable elements is another feasible ways for increasing the system reliability. Such problem of maximizing system reliability through redundancy and component reliability choices is called "reliability–redundancy allocation problem (RRAP)". The general mathematical formulation of the reliability–redundancy allocation problem is

$$\begin{aligned} \text{Maximize} \quad & R_s(r_1, r_2, \ldots, r_m, n_1, n_2, \ldots, n_m) \\ \text{subject to} \quad & g(r_1, r_2, \ldots, r_m, n_1, n_2, \ldots, n_m) \le b \\ & 0 \le r_i \le 1 \quad ; \quad r_i \in [0,1] \subset \mathbb{R}; \quad i = 1, 2, \ldots, m \\ & 1 \le n_i \le n_{i,max}; \quad n_i \in \mathbb{Z}^+ \end{aligned}$$

where $g(\cdot)$ is the set of constraint functions usually associated with the system's weight, volume and cost; $R_s(\cdot)$ is the objective function for the overall system reliability; r_i and n_i are the reliability and the number of redundant components in the ith subsystem, respectively; m is the number of subsystems in the system and b is the vector of resource limitations. This problem is the mixed-integer programming problem as some of the variables, the number of redundancies n_i, are positive integers and others, component reliabilities r_i, are real numbers between 0 and 1. The main goal of this problem is to determine the number of components' n_i and r_i in each subsystem so as to maximize the overall system reliability. During the last two decades, numerous technique had been designed for solving these problems and classified as implicit enumeration, dynamic programming, branch and bound technique, Lagrangian multiplier method, heuristic methods, etc. [1–7]. But these approaches do not guarantee exact optimal solutions, but they achieve reasonably good solutions for hard problems in relatively short time periods. However, the heuristic techniques require derivatives for all non-linear constraint functions, that are not derived easily because of the high computational complexity. To overcome this difficulty metaheuristics have been selected and successfully applied to handle a number of reliability optimization problems. These heuristics include genetic algorithms (GAs) [8–10], simulated annealing (SA) [11], particle swarm optimization (PSO) [12–15], immune based optimization [16,17], artificial bee colony (ABC) [18,19], cuckoo

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search (CS) [20], harmony search (HS) [21], differential evolution (DE) [22–24], etc.

Biogeography-based optimization (BBO), proposed by [25], is a new entrant in the domain of global optimization based on the theory of biogeography. The basic idea of BBO is based on the biogeography theory, which is the study of the geographical distribution of biological organisms. Different from other population based algorithms, in BBO, poor solutions can improve the qualities by accepting new features from good ones. BBO is developed through simulating the emigration and immigration of species between habitats in the multidimensional solution space, where each habitat represents a candidate solution. Like other evolutionary algorithms, BBO probabilistically shares information between candidate solutions. Biogeography not only gives a description of species distributions, but also a geographical explanation. Biogeography is modeled in terms of such factors as habitat area and immigration rate and emigration rate, and describes the evolution, extinction and migration of species. BBO has certain features in common with other population-based optimization methods like GA and PSO, BBO can share information between solutions. This makes BBO applicable to many of the same types of problems that GAs and PSO are used for, including unimodal, multimodal and deceptive functions. In BBO and PSO, each solution stays survive to the end of optimization procedure, but in most of evolutionary based algorithms, solutions die at the end of each generation. However, BBO also has some unique features that clearly differ from other population-based optimization methods. Also, in some of evolutionary due to crossover step, good solutions lose their efficiency, but in BBO do not have crossover step. One more characteristic of BBO is that its set of solutions is maintained and improved from one generation to the next by migrating. Also, for each generation, BBO uses the fitness of each solution to determine its emigration and immigration rate. Moreover, the structure of BBO is similar to PSO in terms of maintaining the solutions from one iteration to others, but each solution can learn from its neighbors and adapt itself as long as the algorithm progresses. In PSO, the solution is updated indirectly through velocity vector while the solutions of BBO are changed directly via migration from other solutions, i.e., BBO solutions directly share their attributes with other solutions. After tests on many benchmarks, and comparisons with many other widely used heuristic algorithms like GAs, PSO and others, BBO outperformed most of the other algorithms on most of the benchmarks [26–28]. Several variations of BBO have been proposed to enhance the performance of the standard BBO recently [26–32]. Since its introduction, it has been applied to a variety of problems, including economic emission dispatch [29], optimal meter replacement [30], distributed learning [31], power management [32], etc. These studies show that BBO is an algorithm that has much promise and merits further development and investigation.

Since BBO is a new optimization method and the biogeography literature is rich, there is still much room left for further research. In this paper, inspired by variants of biogeography and taking the advantages of BBO over other evolutionary algorithms, we consider the performance of series–parallel systems in the field of reliability optimization model in which we maximize the system reliability retaining the various resources and it has been observed that the results of the new approach are all superior to the existing results in the literature. To the best of our knowledge, BBO is not already applied for solving the RRAP. The remaining paper is structured as follows. In Section 2, we mainly talk about the assumption and notations that have used during the formulation of the four benchmark problems of RRAP namely, series, series–parallel, bridge and overspeed protection systems. In Sections 3 and 4, BBO optimization for solving the RRAP has been discussed along with a penalty method for handling the constraint during the analysis. The final results are discussed in Section 5 while conclusion drawn is discussed in Section 6.

2. Problem formulation: reliability redundancy allocation problem

2.1. Assumptions

- If a component of any subsystem fails to function, the entire system will not be damaged or fail.
- All redundancy is active redundancy with out repair.
- The components and system have only two states – operating state and failure state.

2.2. Notations

m	number of subsystems in the system.
M	number of constraints.
n_i	the number of components in subsystem $i, 1 \le i \le m$.
n	$=(n_1, n_2, \dots, n_m)$, the vector of redundancy allocation for the system.
r_i	reliability of each components in subsystem $i, 1 \le i \le m$.
r	$=(r_1, r_2, \dots, r_m)$, the vector of component reliabilities for the system.
g_j	the j^{th} constraint function, $j = 1, 2, \dots, M$.
w_i	the weight of each component in subsystem $i, 1 \le i \le m$.
c_i	the cost of the each component in subsystem $i, 1 \le i \le m$.
v_i	the volume of each component in subsystem $i, 1 \le i \le m$.
R_i	$= 1-(1-r_i)^{n_i}$ is the reliability of the i^{th} subsystem $1 \le i \le m$.
Q_i	$1-R_i$ is the unreliability of the i^{th} subsystem.
$n_{i,max}$	maximum number of components in subsystem $i, 1 \le i \le m$.
R_s	the system reliability.
C, W	the upper limit of the system's cost, weight respectively.
P_F	search feasible region.
λ	immigration rate.
μ	emigration rate.
E, I	maximum migration and immigration rate respectively.

In the present paper, four benchmark problems of the reliability–redundancy allocation problem have been studied. The first three problems with nonlinear constraints used by Hikita et al. [1], Xu et al. [2], Hsieh et al. [3], Chen [16], Hsieh and You [17], Yeh and Hsieh [18], Garg [33] are a series system, series–parallel system and complex(bridge) system. The fourth problem, investigated by Dhingra [5], Yokota et al. [8], Coelho [13], Chen [16], Hsieh and You [17], Yeh and Hsieh [18], Garg [33] is of overspeed protection system.

All these problems are shown to maximize the system's reliability subject to multiple nonlinear constraints and can be stated as the mixed-integer nonlinear programming problems. For each problem, both the component reliabilities and redundancy allocations are to be decided simultaneously and are formulated as below.

Problem 1. Series system (Fig. 1(a)) [1,3,11,16–18,33,34]

$$\text{Maximize } R_s(r,n) = \prod_{i=1}^{5} [1-(1-r_i)^{n_i}]$$

$$\text{s.t.} \quad g_1(r,n) = \sum_{i=1}^{5} v_i n_i^2 - V \le 0 \tag{1}$$