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Modified imperialist competitive algorithm based on attraction and repulsion concepts for reliability-redundancy optimization

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ABSTRACT

System reliability analysis and optimization are important to efficiently utilize available resources and to develop an optimal system design architecture. System reliability optimization has been solved by using optimization techniques including meta-heuristics. Meanwhile, the development of meta-heuristics has been an active research field of the reliability optimization wherein the redundancy, the component reliability, or both are to be determined. In recent years, a broad class of stochastic meta-heuristics, such as simulated annealing, genetic algorithm, tabu search, ant colony, and particle swarm optimization paradigms, has been developed for reliability-redundancy optimization of systems. Recently, a new kind of evolutionary algorithm called Imperialist Competitive Algorithm (ICA) was proposed. The ICA is based on imperialistic competition where the populations are represented by countries, which are classified as imperialists or colonies. However, the trade-off between the exploration (i.e. the global search) and the exploitation (i.e. the local search) of the search space is critical to the success of the classical ICA approach. An improvement in the ICA by implementing an attraction and repulsion concept during the search for better solutions, the AR-ICA approach, is proposed in this paper. Simulations results demonstrates the AR-ICA is an efficient optimization technique, since it obtained promising solutions for the reliability redundancy allocation problem when compared with the previously best-known results of four different benchmarks for the reliability-redundancy allocation problem presented in the literature.

1. Introduction

The importance of reliability in systems conceptions has been growing with advances on technologies in order to avoid failures. Reliability can be defined as the probability for a system does not fail during an interval of time in which the system must be working. In Zio (2009), the system reliability is stated as the interaction of four elements: hardware, software, organization and human. The reliability redundancy allocation problem takes into account only the hardware project, which is the choice of redundant components and the reliability of each component taking into account the cost, volume and weight constraints.

Different meta-heuristics have been employed to solve the reliability redundancy allocation problem, such as evolutionary algorithms (Coit & Smith, 1996; Gen & Kim, 1999; Gen & Yun, 2006; Khoshgoftaar & Liu, 2007; Salazar & Rocco, 2007; Taguchi, Yokota, & Gen, 1998; Tian & Zuo, 2006; Wang & Li, 2012), tabu search (Konak, Smith, & Coit, 2003; Ouzineb, Nourelfath, & Gendreau, 2008), ant colony optimization (Ahmadizar & Soltanpanah, 2011; Liang & Smith, 2004; Samrout, Yalaoui, Châtelet, & Chebbo, 2005), artificial immune system (Chen & You, 2005), fuzzy system (Mahapatra & Roy, 2006), particle swarm optimization (Yeh, 2009), artificial neural networks (Habib, Alsieidi, & Youssef, 2009), and harmony search (Zou, Gao, Wu, Li, & Li, 2010).

In this paper a recently proposed method based on imperialism called Imperialist Competitive Algorithm (ICA) is used to solve four benchmark problems related to reliability-redundancy optimization. The ICA was recently introduced by Esmaeil and Lucas (2007). Recent papers about applications of ICA approaches, mainly in control systems, have been published. Examples are given by Atashpaz-Gargari, Hashemzadeh, and Lucas (2008), Khabbazi, Atashpaz-Gargari, and Lucas (2009), Nasab, Kherzi, Khodamoradi, and Atashpaz-Gargari (2010), Niknam, Fard, Pourjafarian, and Rousta (2011) Rajabioun, Atashpaz-Gargari, and Lucas (2008), Roshanaei, Atashpaz-Gargari, and Lucas (2008) and Zhang, Wang, and Peng (2009).

ICA is a global optimization technique based on the action of imperialists in attempt to conquer colonies. Like others population based algorithms, the ICA starts with a random generated popula-

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tion called countries. Those countries are divided between imperialists and colonies. The imperialists are the best candidate solution and the colonies are the rest of them. The main action that leads the search for better solutions in the ICA is the colonies movement towards the imperialists. This mechanism makes the population to converge to certain spots in the search space where the best solution founded so far are located.

Many stochastic optimization methods suffer from the premature convergence problem. This problem is caused when the algorithm gets trapped in a local optimum region due to poor exploration of the search space. In *A Diversity Guided Swarm Optimizer* proposed and evaluated in Ursem (2002), Riget and Vesterstrøm (2002), and Ursem (2003), a concept of attraction and repulsion is employed in the particle swarm optimization (PSO) in an attempt to overcome the premature convergence problem. The repulsion phase is activated when the population (swarm) has a low diversity and the individuals (particles) are repelled in order to better explore the search space. When the population reaches a high diversity it switches back to the attraction phase and the individuals return to converge.

Based on these actions, the Attraction and Repulsion ICA (AR-ICA) is proposed and evaluated in this paper. Although instead of using a function to calculate the population's diversity as proposed in the ARPSO, the AR-ICA uses the distance between the colony from its imperialist to alternate between the attraction and repulsion phase.

The remainder of this paper is organized as follows. In Section 2 the reliability-redundancy optimization problem is introduced. The characteristics of ICA and AR-ICA approaches are detailed in Section 3. The problem formulation for reliability-redundancy optimization and its assumptions are given in Section 4. Moreover, Section 4 also presents the simulation results for those optimization problems. Finally, the conclusion and further research are discussed in Section 5.

2. Reliability-redundancy optimization problem

A reliability-redundancy optimization problem can be formulated by choosing the system reliability as the objective function. In this work, the reliability-redundancy allocation problem subject to constraints can be formulated as

$$\text{Maximize } R_s = f(\boldsymbol{r}, \boldsymbol{n}), \tag{1}$$

$$\text{subject to } g(\boldsymbol{r}, \boldsymbol{n}) \leqslant l \tag{2}$$

$$0 \leqslant r_i \leqslant 1, \quad r_i \in \Re,\ n_i \in Z^+,\ 1 \leqslant i \leqslant m.$$

where R_s is the reliability of system, g is the set of constraint functions, which usually are associated with system weight, volume and cost, $\boldsymbol{r} = (r_1, r_2, r_3, \ldots, r_m)$ is the vector of the component reliabilities for the system, $\boldsymbol{n} = (n_1, n_2, n_3, \ldots, n_m)$ is the vector of the redundancy allocation for the system; r_i and n_i are the reliability and the number of components in the ith subsystem respectively; $f(\cdot)$ is the objective function for the overall system reliability; l is the resource limitation; m is the number of subsystems in the system. Our goal is to determine the number of components and the component's reliability in each system so as to maximize the overall system reliability. The problem belongs to the category of constrained nonlinear mixed-integer optimization problems.

The four reliability-redundancy problems evaluated in this paper are formulated, which are outlined in the next subsections.

2.1. Problem 1 (P1): Series system

The first problem example evaluated was presented in Chen (2006) and Hsieh, Chen, and Bricker (1998). Fig. 1 shows the series system analyzed in this paper. The optimization problem of a series system can be stated as (Chen, 2006)

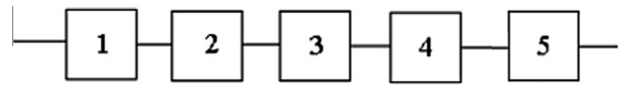

Fig. 1. Representation for the series system.

$$\text{Maximize } f(\boldsymbol{r}, \boldsymbol{n}) = \prod_{i=1}^{m} R_i(n_i) \tag{3}$$

subject to

$$g_1(\boldsymbol{r}, \boldsymbol{n}) = \sum_{i=1}^{m} w_i \cdot v_i^2 \cdot n_i^2 \leqslant V \tag{4}$$

$$g_2(\boldsymbol{r}, \boldsymbol{n}) = \sum_{i=1}^{m} \alpha_i \cdot \left(-\frac{1000}{\ln r_i}\right)^{\beta_i} \cdot \left[n_i + e^{0.25 n_i}\right] \leqslant C \tag{5}$$

$$g_3(\boldsymbol{r}, \boldsymbol{n}) = \sum_{i=1}^{m} w_i \cdot n_i \cdot e^{0.25 n_i} \leqslant W \tag{6}$$

Eqs. (4)–(6) are constraints regarding reliability, system, cost and weight, respectively. The constraint given by (4) is a combination of weight, redundancy allocation and volume; (5) is a cost constraint; and (6) is a weight constraint. In this context, V is the upper limit of the sum of the subsystem's products of volume, C is the upper limit of the cost of the system, and W is the upper limit on the weight of the system, w_i is a factor with constant value for the ith system component; $n_i \in Z^+$, where Z^+ is the discrete space of positive integers, and $0 \leqslant r_i \leqslant 1,\ r_i \in \Re,\ 1 \leqslant i \leqslant m$. The parameters β_i and α_i are physical features of ith system component. The input parameters of the series system described in Chen (2006) and Hsieh et al. (1998) are shown in Table 1.

2.2. Problem 2 (P2): Series–parallel system

The second example problem was evaluated in Chen (2006) and Hsieh et al. (1998). Fig. 2 shows the series–parallel system analyzed in this paper. The optimization problem of series–parallel systems can be stated as (Chen, 2006)

$$\text{Maximize } f(\boldsymbol{r}, \boldsymbol{n}) = 1 - (1 - R_1 R_2)(1 - (1 - R_3)(1 - R_4) R_5) \tag{7}$$

subject to $g_1(\mathbf{r}, \mathbf{n})$, $g_2(\mathbf{r}, \mathbf{n})$, and $g_3(\mathbf{r}, \mathbf{n})$ (see (4)–(6) of the first example),

where $n_i \in Z$, where Z is the discrete space of integers, and $0 \leqslant r_i \leqslant 1,\ r_i \in \Re$, where $\Re$ is set of real numbers, $0 \leqslant i \leqslant m$. The input parameters of the series–parallel system are given in Table 2.

2.3. Problem 3 (P3): Complex (bridge) system

The third problem example, used to demonstrate the efficiency of ICA and AR-ICA approaches, were proposed in Chen (2006), Hikita, Nakagawa, and Harihisa (1992), Hsieh et al. (1998) and Konak et al. (2003). Fig. 3 represents the complex (bridge) system analyzed in this paper. The complex (bridge) system optimization problem can be stated as follows:

Table 1
Data used in series system.

Stage	$10^5 \cdot \alpha_i$	β_i	$w_i \cdot v_i^2$	w_i	V	C	W
1	2.330	1.5	1	7	110	175	200
2	1.450	1.5	2	8			
3	0.541	1.5	3	8			
4	8.050	1.5	4	6			
5	1.950	1.5	2	9			