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A particle-based simplified swarm optimization algorithm for reliability redundancy allocation problems

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ABSTRACT

This paper proposes a new swarm intelligence method known as the Particle-based Simplified Swarm Optimization (PSSO) algorithm while undertaking a modification of the Updating Mechanism (UM), called N-UM and R-UM, and simultaneously applying an Orthogonal Array Test (OA) to solve reliability–redundancy allocation problems (RRAPs) successfully. One difficulty of RRAP is the need to maximize system reliability in cases where the number of redundant components and the reliability of corresponding components in each subsystem are simultaneously decided with nonlinear constraints. In this paper, four RRAP benchmarks are used to display the applicability of the proposed PSSO that advances the strengths of both PSO and SSO to enable optimizing the RRAP that belongs to mixed-integer nonlinear programming. When the computational results are compared with those of previously developed algorithms in existing literature, the findings indicate that the proposed PSSO is highly competitive and performs well.

1. Introduction

System reliability optimization has been a popular research area that has received significant attention over the past several decades [1–11] due to its critical importance in various types of systems. It has been extensively used in many real-world applications such as computer and communication systems, power systems, and transportation systems [3–5,11]. Thus, system reliability plays a very important role in modern society [1–11].

The main goal of reliability engineering is to increase system reliability. In general, there are two methods that are used to increase system reliability: the first increases the reliability of components and the second uses redundant components within subsystems. The use of redundant components in subsystems is the direct and the most common method of enhancing system reliability in industrial engineering activities. A majority of the work in system reliability is devoted to solving redundancy allocation problems (RAP) for which the decision variables are redundancy levels that can be expressed as integer values [7,8,12].

A reliability–redundancy allocation problem (RRAP) is a classic optimization problem that seeks to maximize system reliability through RAP [9]. To optimize a system RRAP, component reliabilities are denoted as continuous values that fall between zero and one, whereas redundancy levels are integer values. Thus, RRAP is a mixed-integer programming approach with the goal of maximizing system reliability under constraints such as the system cost, weight, and volume.

Researchers have not only studied comprehensive RRAP-related works, such as those of Kuo & Prasad and Kou et al. [8,10], but have also focused on developing heuristic optimization algorithms to optimize RRAP reliability. For example, the Artificial bee colony algorithm [1], the Genetic algorithms [6,13,15], the Ant system [14], the Immune algorithm [16,17], combinations of several heuristics [10,18], and the Surrogate constraints algorithm [2,19] have all been employed to address RRAP. In this RRAP-related literature, a minority of the system reliability–redundancy allocation problems have been subjected to linear constraints [20,21], whereas the majority have been subjected to nonlinear constraints [1,2,6,13,15–19,22].

RRAP has been developed with the consideration of various approaches. However, RRAP is a powerful tool and a very important technique for engineering systems. Thus, sustained progress in optimization reliability via RRAP is an important goal.

The particle swarm optimization (PSO) algorithm developed by Kennedy and Eberhard [23] and simplified swarm optimization (SSO) algorithm developed by Yeh [24–27] are both population-based stochastic optimization methods belonging to the category of swarm intelligence methods; they are used to search for the optimum in real numbers and in discrete numbers, respectively [23–27]. Based on the strengths of both PSO and SSO, a novel particle-based simplified swarm optimization algorithm that is based on PSO and SSO is developed in this paper to optimize RRAP. Thus, this study contributes to RRAP solutions by focusing on the

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Notations

N_{var}, N_{sol}, N_{gen} the number of subsystems in the system, solutions, and generations, respectively
N $\mathbf{N}=(n_1, n_2,\ldots,n_{N_{\text{var}}})$ is the redundancy allocation vector of the system, where n_i is the number of components in subsystem i for $i=1,2,\ldots,N_{\text{var}}$
R $\mathbf{R}=(r_1, r_2,\ldots,r_{N_{\text{var}}})$ is the component reliability vector of the system, where r_i is the reliability of each component in subsystem i for $i=1,2,\ldots,N_{\text{var}}$
$R_i(n_i)$, q_i $R_i(n_i)=1-q_i^{n_i}$ is the reliability of subsystem i, where $q_i=1-r_i$ is the failure probability of each component in subsystem i for $i=1,2,\ldots,N_{\text{var}}$
R_s the system reliability
$g_j(\mathbf{R}, \mathbf{N})$ the jth constraint function w.r.t. **R** and **N**
α_i, β_i the physical feature of each component in subsystem i for $i=1,2,\ldots,N_{\text{var}}$
l_j the resource limitation for the jth constraint function
v_i, c_i, w_i the volume, cost, and weight of each component in subsystem i, respectively, $i=1,2,\ldots,N_{\text{var}}$
V, C, W the upper limit on the volume, cost, and weight of the system, respectively
$f(\mathbf{R}, \mathbf{N})$ the fitness function w.r.t. **R** and **N**

$N_{\text{sol}}^{\text{gen}}$, $n_{\text{sol,var}}^{\text{gen}}$ $N_{\text{sol}}^{\text{gen}}=(n_{\text{sol},1}^{\text{gen}}, n_{\text{sol},2}^{\text{gen}}, \ldots, n_{\text{sol,Nvar}}^{\text{gen}})$ is the redundancy allocation vector of the sol$^{\text{th}}$ solution at the gen$^{\text{th}}$ generation, where $n_{\text{sol,var}}^{\text{gen}}$ is the var$^{\text{th}}$ variable for $var=1,2,\ldots,N_{\text{var}}$

$R_{\text{sol}}^{\text{gen}}$, $r_{\text{sol,var}}^{\text{gen}}$ $R_{\text{sol}}^{\text{gen}}=(r_{\text{sol},1}^{\text{gen}}, r_{\text{sol},2}^{\text{gen}}, \ldots, r_{\text{sol,Nvar}}^{\text{gen}})$ is the component reliability vector of the sol$^{\text{th}}$ solution at the gen$^{\text{th}}$ generation, where $r_{\text{sol,var}}^{\text{gen}}$ is the var$^{\text{th}}$ variable for $var=1,2,\ldots,N_{\text{var}}$

$X_{\text{sol}}^{\text{gen}}$ $X_{\text{sol}}^{\text{gen}}=(N_{\text{sol}}^{\text{gen}},R_{\text{sol}}^{\text{gen}})$ is the sol$^{\text{th}}$ solution at the gen$^{\text{th}}$ generation
$\widehat{n}_{\text{sol}}$, $\widehat{n}_{gBest}$ the related *pBest* and *gBest* for the *N*-UM, e.g., $\widehat{n}_{\text{sol}}$, is the *pBest* of the sol$^{\text{th}}$ solution, and $f(\widehat{n}_{gBest})$ is the fitness value of the *gBest*
$\widehat{R}_{\text{sol}}$, $\widehat{R}_{gBest}$ the related *pBest* and *gBest* for the R-UM, e.g., $\widehat{R}_{\text{sol}}$, is the *pBest* of the sol$^{\text{th}}$ solution, and $f(\widehat{R}_{gBest})$ is the fitness value of the *gBest*
C_{UB}, W_{UB} V_{UB} The upper bound of the required cost, weight, and volume, respectively
C, W, V the cost, weight, and volume, respectively
R_p penalized system reliability

Updating Mechanism (UM), called N-UM and R-UM, which updates the variables of component numbers that are discrete numbers and the variables of components reliabilities that are real numbers, respectively. Furthermore, an Orthogonal Array Test (OA) is implemented to efficiently determine the best combination of the related parameters used in the UMs. The proposed PSSO algorithm, along with the UMs and the OA, is then presented and its effectiveness is demonstrated by considering four benchmarks via mixed-integer programming with multiple nonlinear constraints: a series system in benchmark 1, a network with series and parallel elements in benchmark 2, a complex (bridge) system in benchmark 3, and the overspeed protection of a gas turbine system in benchmark 4 [1,17]. The related introduction of RRAP programming, PSO, and SSO is outlined in the following sections.

Section 2 provides the definition of RRAP and its four benchmarks. Section 3 presents an overview of PSO and SSO. Section 4 describes the N-UM, R-UM, and the proposed PSSO algorithm. An orthogonal array test is presented in Section 5. A description of the four benchmarks and the results of the experiments are demonstrated in Section 6. Finally, the conclusions are presented in Section 7.

2. Definition of RRAP and four benchmarks

RRAP has become an increasingly powerful tool in the initial stages of the planning, design, and control of systems. The goal of RRAP is to maximize overall system reliability by determining both the number and reliability of components in each subsystem under multiple nonlinear constraints. This problem can be categorized under mixed-integer nonlinear optimization and defined as follows:

$$\text{Maximize } R_s = f(\mathbf{R}, \mathbf{N}) \tag{1}$$

$$\text{Subject to} \quad g_j(\mathbf{R}, \mathbf{N}) \le l_j$$

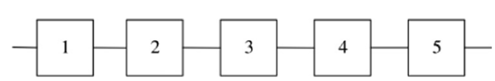

Fig. 1. The series system.

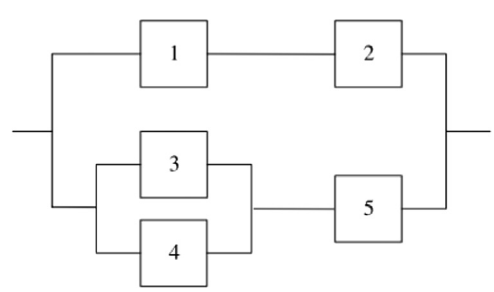

Fig. 2. The network with series and parallel elements.