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A practical approach for solving multi-objective reliability redundancy allocation problems using extended bare-bones particle swarm optimization

Enze Zhang, Yifei Wu*, Qingwei Chen

School of Automation, Nanjing University of Science and Technology, Nanjing 210094, China

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ABSTRACT

This paper proposes a practical approach, combining bare-bones particle swarm optimization and sensitivity-based clustering for solving multi-objective reliability redundancy allocation problems (RAPs). A two-stage process is performed to identify promising solutions. Specifically, a new bare-bones multi-objective particle swarm optimization algorithm (BBMOPSO) is developed and applied in the first stage to identify a Pareto-optimal set. This algorithm mainly differs from other multi-objective particle swarm optimization algorithms in the parameter-free particle updating strategy, which is especially suitable for handling the complexity and nonlinearity of RAPs. Moreover, by utilizing an approach based on the adaptive grid to update the global particle leaders, a mutation operator to improve the exploration ability and an effective constraint handling strategy, the integrated BBMOPSO algorithm can generate excellent approximation of the true Pareto-optimal front for RAPs. This is followed by a data clustering technique based on difference sensitivity in the second stage to prune the obtained Pareto-optimal set and obtain a small, workable sized set of promising solutions for system implementation. Two illustrative examples are presented to show the feasibility and effectiveness of the proposed approach.

1. Introduction

Multiple objectives are often considered simultaneously in practical problems concerning with system design. The redundancy allocation problem (RAP) requires the simultaneously optimization of objective functions such as system reliability, cost and weight, when determining the optimal system design configuration given certain design constraints. It involves the selection of components from among several types of component choices with different levels of cost, reliability, weight and other characteristics. The incorporation of redundant components improves system reliability, but can also increase system cost, weight, etc. Thus, a RAP frequently encounters a trade-off between maximization of system reliability and minimization of system cost and weight.

Traditionally, most researchers studying RAP have focused on single-objective optimization. The RAP is either solved as a single objective optimization problem with the goal to maximize the system reliability, subject to several constraints such as weight and cost, or transformed into a single objective optimization problem through summing the multiple objectives into a single objective with respective weight. Numerous researchers have addressed several methodologies and approaches to handle it, including dynamic programming [1–3], integer programming [4–6], mixed integer and non-linear programming [7], the column generation method [8], and meta-heuristics such as genetic algorithms (GAs) [9–14], tabu search [15,16], and ant colony optimization [17,18].

These studies focusing on single-objective optimization have their own advantages. However, in practice, multiple considerations have to be taken into account when determining the redundancy allocation of the system. In this context, these studies fail to represent the nature of the RAP, without providing any information regarding the tradeoff front. Also, aggregating multiple objectives into a single objective to obtain promising results is a challenge as the values of the weights might affect the set of non-dominated solutions found [19,20] and need to be modified each time to re-compute the corresponding solution. To cope with these drawbacks, other multi-objective optimization approaches have been used to solve the RAP to determine an entire Pareto optimal solution set.

Recent work has demonstrated the effectiveness of the meta-heuristic algorithms for solving the multi-objective RAPs [21–27]. In [22], a multi-objective GA was used to solve a RAP in a safety system. In [19], the authors formulated the RAP as a multi-objective problem

* Corresponding author. Tel.: +86 13851792312.
E-mail addresses: yzzez8986@gmail.com (E. Zhang), wuyifei@mail.njust.edu.cn (Y. Wu).

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and solved this problem using the non-dominated sorting genetic algorithm (NSGA). In [24], a multi-objective evolutionary algorithm (EA) is applied to identify the Pareto optimal set of the RAP. In [25], the authors employed a problem-specific EA to solve the continuous reliability optimization problems where the decision variable is the reliability of the components. Recently, a variant of the non-dominated sorting genetic algorithm (NSGA-II) was proposed in [26] to solve a novel mathematical model for multi-objective RAPs.

Particle swarm optimization (PSO), first introduced by Kennedy and Eberhart [28], is a population-based heuristic search technique inspired by the paradigm of birds flocking. Due to its simplicity, fast convergence and robustness, PSO has been successfully used to solve single-objective optimization design problems. These features motivated researchers to extend PSO to multi-objective problems, and recently, several PSO-based algorithms [29,30] have been proposed to solve the multi-objective RAPs. However, these approaches require tuning control parameters such as inertia weight and acceleration coefficients in order to obtain desirable solutions, and this could be a limitation while being used to solve real world problems [31]. Moreover, empirical and theoretical studies have shown that the convergence behavior of PSO depends strongly on the values of these control parameters [32,33]. In this context, PSO does not perform well in its research in complex constrained solution spaces, which is the case for many complex real-world problems, in particular, the RAP.

In this paper, a novel multi-objective optimization algorithm, called the bare-bones multi-objective particle swarm optimization (BBMOPSO) is proposed for solving the RAP. To overcome the limitations of PSO, we adopt the bare-bones particle swarm optimization (BBPSO) to handle the complexity and nonlinearity of the RAP. Unlike the PSO, the BBPSO has a particle updating strategy which does not require tuning up control parameters and is suitable for those real application problems where information on parameters is lacking or hard to obtain. There are some studies in the literature [34–36] which have been done to apply the BBPSO to single-objective problems. However, in the case of multi-objective optimization problems, a few applications can be found, and one of those is in [37], which uses the BBMOPSO to deal with the multi-objective environmental/economic dispatch (EED) problem. In this study, we present a bare-bones multi-objective particle swarm optimization algorithm for solving the RAP. To extend the bare-bones PSO to the multi-objective optimization problems, we make some modifications as follows. An approach based on the adaptive grid is adopted to update the global particle leaders, and a mutation operator with action range varying over time is introduced to improve the exploration ability. In addition, a constraints handling technique especially suitable for inequality constraints is used.

For multi-objective problems, in general no unique solution exists there, but a set of Pareto optimal solutions including all rational choices, among which the decision-maker has to ultimately select one or a small set of solutions to be further considered. Often this set can be huge, and it is one challenging problem to prune it to produce a set of promising solutions for implementation [19,24]. After identifying the Pareto optimal solution set by applying the BBMOPSO, we group the prospective solutions into clusters using the clustering technique based on the difference sensitivity. Clusters are formed in such a way that objects in the same cluster are similar and objects in different clusters are distinct, and measures of similarity depend on the difference sensitivity defined. Then we focus our research on solutions of the cluster from the “knee” region, which contains the most promising solutions. The resulting pruned Pareto set is simply a non-dominated subset of a more manageable size to offer meaningful design options.

The rest of paper is organized as follows. Section 2 introduces the major concepts in multi-objective optimization algorithms. Section 3 formulates the target RAP problem including its multiple objectives as well as design constraints. The proposed BBMOPSO algorithm and the sensitivity-based data clustering method are discussed in detail in Sections 4 and 5, respectively. A numerical example is presented in Section 6 to demonstrate the effectiveness of the proposed algorithm as well as the clustering method in solving multi-objective RAP. The conclusion and remarks are given in Section 7.

2. Multi-objective optimization

Very often real-world problems have several conflicting objectives. Even though many of them can be reduced to a matter of a single objective, it may not adequately represent the problem being faced. Considering multiple objectives often gives better ideas of the task. If so, there is a vector of objectives involving m (≥ 2) conflicting objective functions $f_i : \mathbf{R}^n \rightarrow \mathbf{R}$ that must be traded off in some way. Multi-objective optimization is concerned with the minimization of $\mathbf{F}(\mathbf{x})$ that can be the subject of a number of inequality and equality constraints:

$$\begin{aligned} &\min_{\mathbf{x} \in \mathbf{R}^n} \mathbf{F}(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_m(\mathbf{x})) \\ &\text{subject to} \\ &g_j(\mathbf{x}) \leq 0, \quad j = 1, 2, \ldots, J \\ &h_k(\mathbf{x}) = 0, \quad k = 1, 2, \ldots, K \end{aligned} \tag{1}$$

The decision vectors $\mathbf{x} = (x_1, x_2, \ldots, x_n)$ belong to the feasible region $S \subset \mathbf{R}^n$ which is formed by constraint functions.

Note that because $\mathbf{F}(\mathbf{x})$ is a vector, if any of the components of $\mathbf{F}(\mathbf{x})$ are competing, there is no unique solution to this problem. Therefore, it is necessary to establish certain criteria to determine what is considered as an optimal solution, and this criterion is non-dominance. Thus, solutions to a multi-objective optimization problem are mathematically expressed in terms of non-dominance.

Without loss of generality, in a minimization problem, for feasible solutions $\mathbf{x}_1$ and $\mathbf{x}_2$, $\mathbf{x}_1$ is said to dominate $\mathbf{x}_2$ (denoted by $\mathbf{x}_1 \prec \mathbf{x}_2$), if and only if both of the following conditions are true:

- $\mathbf{x}_1$ is no worse than $\mathbf{x}_2$ in all objectives, i.e., $f_i(\mathbf{x}_1) \leq f_i(\mathbf{x}_2)$ for all $i = 1, 2, \ldots, m$.
- $\mathbf{x}_1$ is strictly better than $\mathbf{x}_2$ in at least one objective, i.e., $f_i(\mathbf{x}_1) < f_i(\mathbf{x}_2)$ for at least one i.

A feasible solution $\mathbf{x}$ is said to be non-dominated with respect to set Ω, if there does not exist $\mathbf{x}'$ such that $\mathbf{x}' \prec \mathbf{x}$. Furthermore, the feasible solutions that are non-dominated within the entire search space are called the *Pareto optimal* solutions, which constitute the Pareto optimal set. Unless there is some preference information, the main goal of the multi-objective optimization problem is to find a Pareto-optimal set, instead of a single optimal solution. The detailed discussion of these basic concepts can be found in [31,38].

3. Redundancy allocation problem (RAP)

The RAP is a system design optimization problem, which pertains to a system of s subsystems arranged in series. For each subsystem, there are n_i functionally equivalent components arranged in parallel. Each component potentially varies in reliability, cost, weight and other characteristics. The n_i components are to be selected from m_i available component types where multiple copies of each type can be selected. A minimum of one