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A knowledge-based archive multi-objective simulated annealing algorithm to optimize series–parallel system with choice of redundancy strategies ☆

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ABSTRACT

Redundancy allocation problem (RAP) is one of the best-developed problems in reliability engineering studies. This problem follows to optimize the reliability of a system containing s sub-systems under different constraints, including cost, weight, and volume restrictions using redundant components for each sub-system. Various solving methodologies have been used to optimize this problem, including exact, heuristic, and meta-heuristic algorithms. In this paper, an efficient multi-objective meta-heuristic algorithm based on simulated annealing (SA) is developed to solve multi-objective RAP (MORAP). This algorithm is knowledge-based archive multi-objective simulated annealing (KBAMOSA). KBAMOSA applies a memory matrix to reinforce the neighborhood structure to achieve better quality solutions. The results analysis and comparisons demonstrate the performance of the proposed algorithm for solving MORAP.

1. Introduction

Redundancy allocation problem (RAP) works on a system containing s sub-systems which connected serially. In sub-system i,n_i parallel components connected together and m_i different component types are available to be allocated. The components parameters like cost, weight, and reliability are also constant. If one type of components is selected for allocating to a sub-system, all components on the mentioned sub-system must be the same type. Moreover, the redundancy strategy of the sub-systems is the system variables and can be either active or cold-standby. Fig. 1 presents the structure of the system.

Many research works in solving methodologies of RAP have been carried out in discrete and continues optimization area. Fyffe, Hines, and Lee (1968) introduced a mathematical model of RAP with active redundancy strategy. The objective function of their model was to maximize system reliability under cost and weight constraints and they solved the problem using dynamic programming. Nakagawa and Miyazaki (1981) presented a non-linear RAP and solved the presented model using a surrogate constraint algorithm and shown that this model is more effective for solving multi-constraint RAP. Coit (2001) developed a model based on integer programming for cold-standby redundancy strategy. Ramirez-Marquez and Coit (2004) presented a heuristic algorithm for multi-state series–parallel RAP. Ramirez-Marquez, Coit, and Konak (2004) presented a Max–Min approach for solving RAP. Tian and Zuo (2006) solved the RAP using physical programming approach. Tavakkoli-Moghaddam, Safari, and Sassani (2008) optimize the series–parallel systems with a choice of redundancy strategies using GA.

In most of the studies in RAP, the redundancy strategy of the sub-systems is predefined. For example, Tillman, Hwang, and Kuo (1977) reviewed 144 papers in RAP and only 14 papers designated the cold-standby redundancy strategy. Considering the redundancy strategy as a system variable, draws RAP near to the real situation. Coit (2003) considered the redundancy strategy of the sub-systems as the system variables for RAP without the choice of selecting different components in each sub-system. Thus, the variables of his model were the number of the components in each sub-system and the sub-systems redundancy strategy. He used integer programming for solving the mathematical model.

As Chern (1972) proved that RAP belongs to NP-Hard problems, heuristic and meta-heuristic algorithms have been widely used to

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Nomenclature

s	number of sub-systems
n_i	number of components in sub-systems i
$n_{Max,i}$	upper bound of allocated component in sub-system i
m_i	number of available components in sub-system i
z_i	selected component index in sub-system i, $z_i \in (1, 2, \ldots, m_i)$
Z	set of z_i, $Z = (z_1, z_2, \ldots, z_s)$
t	operation time
$R(t,z,n)$	system reliability at the time t for design vector z and n
$\widetilde{R}(t,z,n)$	an estimate for $R(t,z,n)$:
$r_{ij}(t)$	reliability of j^{sty} component type in sub-system i at time t
λ_{ij}	shape parameter of Gama distribution
k_{ij}	scale parameter of Gama distribution
C	maximum acceptable cost of system
W	maximum acceptable weight of system
c_{ij}	cost of j^{sty} component in sub-system i
w_{ij}	weight of j^{sty} component in sub-system i
$\rho_i(t)$	continuous detect switch in sub-system i at time t
ρ_i	failure detect switch in sub-system i
$\sigma_i(t,j)$	$\begin{cases} 1; & \text{Perfect switch} \\ \rho_i(t); & \text{Switch reliability at time } t \\ \rho_i^{j-1}; & \text{Switch active when a defect causes} \end{cases}$

solve this problem. Coit and Smith (1996) solved the series–parallel RAP using genetic algorithms (GA). Kim and Gen (1999) used a hybrid GA for solving RAP. Kulturel-Konak, Smith, and Coit (2003) used Tabu search for solving RAP. Liang and Smith (2004) solved the problem with ant colony optimization (ACO) algorithm. Liang and Chen (2007) used variable neighborhood search (VNS) algorithm for solving RAP. Chambari, Najafi, Rahmati, and Karimi (2013) presented an efficient simulated annealing (SA) for solving RAP. Nowadays, various soft-computing approaches are presented and developed to optimize the problem (Alaghebandha and Hajipour; Mousavi, Hajipour, Niaki, and Alikar, 2013; Hajipour, Khodakarami, and Tavana, 2014; Pasandideh et al., 2013). This paper is also developing a novel soft-computing approach based on SA.

All above mentioned algorithms faced with RAP as a single objective problem. In fact, in all of the mentioned researches, the objective function was to maximize the system reliability or minimize the system design cost. Some researchers noticed that to determine the system redundancy more than one aspect must be considered. For example, one might be interested in achieving high reliability with low system cost in the system design phase. In this case, they considered the reliability and the system cost as two unique scalar objectives and after merging these two objectives for a new one, optimized this new objective with single objective technique. For more details about these techniques, one can refer to Misra (1991), Misra and Sharma (1991), Dhingra (1992), Sasaki and Gen (2003a, 2003b), and Zafiropoulos and Dialynas (2004). It is valuable to achieve more effective techniques for solving RAP. The techniques for integrating the objectives are very complicated and reduce the solution region and hence, practically fewer choices are available for decision makers. Taboada, Espiritu, and Coit (2008) presented a multi-objective multi-state GA (MOMS-GA) to find the Pareto fronts. The objectives were maximizing system availability and minimizing system cost and weight, simultaneously. Honak, Coit, and Baheranwala (2008) presented multiple prioritized objectives for a bi-objective model with system availability and minimizing system cost. They used Monte Carlo simulation technique to find Pareto optimal solutions. Safari (2012) proposed a variant of the non-dominated sorting GA (NSGA-II) to solve a mathematical model for multi-objective RAP (MORAP) with a choice of redundancy strategies. Chambari, Rahmati, Najafi, and Karimi (2012) presented a bi-objective model to optimize both reliability and cost of system with a choice of redundancy strategies and proposed multi-objective particle swarm optimization and NSGA-II to solve it. Soltani, Sadjadi, and Tofigh (2014) proposed a new model for RAPs by considering discount policy. The proposed model attempts to maximize the reliability of a system by gathering various components where there are some limitations on budgeting. Some heuristics and meta-heuristics are designed to solve the resulted models. Zoulfaghari, Zeinal Hamadani, and Abouei Ardakan (2014) introduced a new Mixed Integer Nonlinear Programming (MINLP) model to analyze the availability optimization of a system with a given structure, using both repairable and non-repair able components, simultaneously. Yeh (2014) presented a novel orthogonal simplified swarm optimization scheme (OSSO) that combines repetitive orthogonal array testing (ROA), re-initialize population (RIP), and SSO for solving series–parallel RAP with a mix of components. Zhang, Wu, and Chen (2014) proposed a practical approach, combining bare-bones particle swarm optimization and sensitivity-based clustering for solving multi-objective reliability RAPs.

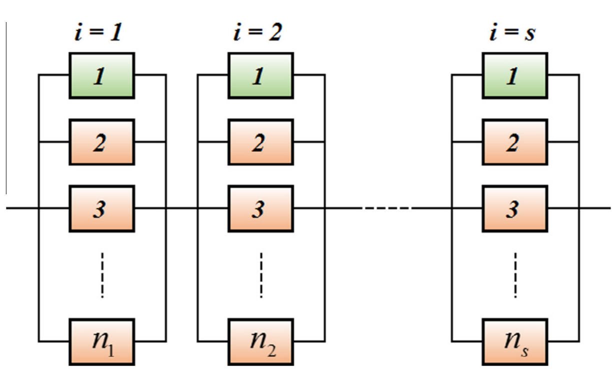

Fig. 1. The system structure.

In this paper, we follow to develop an efficient Pareto-based multi-objective optimization algorithm based on SA called knowledge-based archive multi-objective SA (KBAMOSA) to improve the results of MORAP. In traditional AMOSA, introduced by Bandyopadhyay, Saha, Maulik, and Deb (2008), the amount of dominance has been defined in terms of hyper-volume in objective space enclosed by the points to be compared. The acceptance scheme is based on the exhaustive possible cases on the domination status between the current solution, trial solution, and the solutions in the existing archive of non-dominated solutions. Comparisons have been presented with NSGA-II, Pareto archived evolution strategy (PAES), and multi-objective SA (MOSA) on a number of benchmark problems in order to establish the benefits of their approach. A population based multi-objective simulated annealing algorithm for obtaining transparent models of chaotic systems has been proposed by Sánchez and Villar (2008), where a number of solutions are annealed simultaneously, and the ranking and selection is done based on Pareto dominance. Another novel enhancement in multi-objective simulated annealing has been proposed in Suman, Hoda, and Jha (2010). In their work, they build upon Suppapitnarm's SA (Suppapitnarm, Seffen, Parks, & Clarkson, 2000) by searching along directions based on orthogonal experimental design rather than mutating the solutions randomly.