Reliability Engineering and System Safety 244 (2024) 109835

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

A novel evolutionary solution approach for many-objective reliability-redundancy allocation problem based on objective prioritization and constraint optimization

Rahul Nath [a,*], Pranab K. Muhuri [b]

[a] Department of Informatics, University of Bergen, Thormøhlens Gate 55, Bergen 5008, Norway
[b] Department of Computer Science, South Asian University, Rajpur Road, Maidan Garhi, New Delhi 110068, India

ARTICLE INFO

Keywords:
Many-objective optimization
Reliability-redundancy allocation problem (RRAP)
Evolutionary algorithm
Evolutionary optimization
Objective prioritization

ABSTRACT

The reliability redundancy allocation problem (RRAP) has been mostly solved either as a single or as a multi-objective optimization problem. However, this problem also has numerous important constraints which play prominent roles in meeting the objectives. This paper proposes a novel formulation named 'prioritized many reliability redundancy allocation problems (PrMaORRAP)' that optimizes all the problem objectives concurrently, and also preserves the priority among them. Then, we propose a hybrid method which utilizes the features of many-objective optimization as well as priority relations between different objectives. Here, we divide the procedure into two modules: one is the main priority or the leader which will stay at the top level; underneath the first lie the second part in which rest of the objectives are optimized. The solution approach embeds the optimization structure within the evolutionary process making a prioritized many-objective evolutionary algorithms. We formulate various structures such as series, series-parallel, complex bridge and overspeed gas turbine system of RRAP as many-objective optimization problems, and provide detailed experimental demonstration on how our proposed model works for all these structures. We compare the results given by the proposed approach with the results of other approaches available in the literature and establish the superiority of our proposed solution approach.

1. Introduction

Optimization problems are often classified as single objective, multi-objective and many-objective problems, based on the number of available objectives in those problems. Single objective optimization problems, as the name suggests, contain only one objective. In multi-objective optimization problems, number of objectives are either two or three. If the number of objectives in a problem is more than three, then such problems are called many-objective optimization problems [1]. However, irrespective of the number of available objectives, such optimization problems are difficult to solve because of the high computational complexity [2]. Accordingly, since last few decades, researchers usually consider evolutionary and metaheuristic-based approaches to solve those optimization problems [3]. However, the prime domains where evolutionary approaches have found their wider use by now are single objective and multi-objective optimization problems. This is because there were hardly any available evolutionary approaches to solve many-objective optimization problems until last few years. Though researchers attempted to solve the many-objective optimization problems using available multi-objective evolutionary approaches, the outcomes were hardly satisfactory. This is because, the performance of multi-objective evolutionary approaches (specifically, their ability in finding better solutions) starts deteriorating as the number of objectives goes beyond three [3]. It affects the selection pressure, and the density estimation in the high-dimensional objective space, resulting non-convergence of the population.

Due to the surge in the number of objectives in real-life problems, the number of dominated solutions decreases. If a solution has the best value for one objective and worst for the rest, then that solution will be considered as a non-dominated solution. Therefore, the surge in the number of objectives increases the number of partially good solutions. Accordingly, when more and more solutions become non-dominated, then it becomes very difficult to find better solutions since they are no longer distinguishable based upon the dominance. Furthermore, the

* Corresponding author.
E-mail address: rahul.nath@uib.no (R. Nath).

https://doi.org/10.1016/j.ress.2023.109835
Received 21 December 2022; Received in revised form 13 October 2023; Accepted 18 November 2023
Available online 23 November 2023

density estimator functions, like crowding distance becomes inefficient because the solutions which are not nearer to the Pareto area gets picked up as they are also less dense. This results in the slower convergence or non-convergence of the population most of the time.

To increase the selection pressure, researchers attempted to find alternate method like partial dominance [4], ε-dominace [5], fuzzy dominance [6], decomposition and reference point selection, [1,7], etc. Accordingly, a number of research works on evolutionary approaches were reported recently. One such approaches is the 'multi-objective evolutionary algorithm based on decomposition (MOEA/D)', where inefficiency of selection pressure is tackled by decomposing the solutions in several sub-problems and introducing the reference point [7]. This approach can solve the problem of dominance in higher dimensions; but it is not quite efficient to handle the diversity because some good solutions may dominate most of the sub-problems [8]. There are also popular approaches which use Pareto dominance like 'non-dominated sorting genetic algorithm-II (NSGA-II)' and 'strength Pareto evolutionary archive 2 (SPEA2)'.

In Ref. [9], hypervolume was used as ranking of solutions for solving many-objective optimization problems. To predict the convergence of population while proposing a procedure to solve many-objective problems, the concept of evolution path was used in Ref. [10]. A reference direction-based density estimation with improved assignment and selection strategy was used in Ref. [11] to handle multi and many-objective problems. The idea of maximum vector angle first and worst estimation principles for many-objective problems was used in Ref. [12]. Knee points were also used as reference to solve many-objective problems [13].

A reference point-based non-dominated sorting genetic algorithm called 'non-dominated sorting genetic algorithm-III (NSGA-III)' was proposed in Ref. [1] for solving many-objective problems. Here, to maintain diversity rather than crowding distance, counting of associated solutions with reference point was used to facilitate the density estimation in higher dimensions. This approach was just an extension of NSGA-II, where reference points are generated with respect to the available objectives in addition to the non-dominated sorting. Here, all the solutions are normalized to fit the plane bounded by the reference point. To counter the selection pressure and the density problem, both Pareto dominance (like one used in NSGA-II and SPEA2) and the decomposition (such as one used in MOEA/D) are used in NSGA-III. Accordingly, NSGA-III is now considered as one of the representative evolutionary algorithms to solve the many-objective optimization problems. It has attracted notable praise from the scientific community and are being applied in diverse domains every day. Thus, in a new trend and for practical need, many real-world problems are currently being studied as many-objective optimization problems [14–16].

The reliability redundancy allocation problem (RRAP) has often been solved as a multi-objective problem. In addition to obtaining the desirable value of reliability, there is a need to optimize all the objectives simultaneously. Therefore, recently, effort has also been made to study RRAP as a many-objective optimization problem [17]. Unfortunately, one of the crucial aspects of such optimization problems in the practical domains, which was rarely addressed by the researchers, is the fact that not all the objectives in those problems are of same priority. More specifically, there are clear needs to have a closer look at the underlying importance and priorities that exist among the objectives of the real-life optimization problems. A situation which is often overlooked by the designers at the designing or modelling phase of a system. Accordingly, in many cases, designers as well as the users had to settle for less suitable solutions away from their optima, if not outside of their feasible regions [2,18]. For example, if a civil engineer is assigned to make structure design, there is no need of personal decision but a value judgement. This is because the integrity of the structure results in saving of lives in case of catastrophic events. So, there is a need for a preference-based solutions upon the value judgements integrated in the optimization of the structure design. Another example is modelling a dam on river, where there is a need of choosing flood control and water supply control which help in saving the structural loss and human life. In another case, for example, if in the radioactive waste material disposable process, preference is given to save costs, it may have adverse health effect [19]. Therefore, we clearly see that based upon the environment and resource availability, preference changes. These preferences play a crucial role in robust and safe system designing.

Table 1
Notations and symbols.

Notation	Description	Notation	Description
m	Number of sub-systems	f	Fitness function
r_i	Component reliability	N	Number of objectives
n_i	No. of component	P	Population
w_i	Component weight	P^a	New solutions
v_i	Component volume	C	Maximum cost
R_S	System reliability	W	Maximum weight
C_S	System cost	V	Maximum volume
W_S	System weight	α_i	Scaling factor of the *i*th component
V_S	System volume	β_i	Shaping factor of the *i*th component

In multi-objective optimization, the final solution is a set of Pareto optimal solutions. But to obtain a single solution, designers had to select based upon the preferences. That is, with preferences in the multi-objective optimization, the expected solution may be obtained [20]. Using preferences in the initial phase allow the optimizer to find a solution in accordance with the provided preferences, and it also provides a single solution. The decision maker usually has a better idea of the situation as well as the relative importance of the preferences, in advance. However, just adding preferences do not result in the optimal values of all the objectives. Thus, in this paper, we target both of these aspects and model the reliability redundancy allocation problem as a prioritized many-objective optimization problem. This is because, in real world scenarios, we have to give priority to make user-specific and sustainable systems. So, in order to optimize all the objectives of the RRAP, and also to preserve the priorities among the objectives, we propose a novel formulation named 'prioritized many reliability redundancy allocation problems (PrMaORRAP). Then, to achieve the prioritized many-objective optimization while solving, we propose a hybrid method which utilizes the features of many-objective optimization as well as the priority relations between different objectives. We have divided the procedure into two modules: one is the main priority or the leader which will stay at the top level; underneath the first lie the second part in which rest of the objectives are optimized. This optimization structure is embedded in the evolutionary process making a prioritized many-objective evolutionary algorithm. Furthermore, working of the approach is demonstrated through a detailed experimental investigation. We have extensively compared the results given by the proposed approach with the results of other approaches available in the literature. For experimentations with the proposed approach, four case studies (system structures): series, series-parallel, complex bridge and overspeed protection system for gas turbine are considered. All the four case studies have common objectives: maximization of reliability and minimization of cost, weight, and volume. The priority of reliability is higher than other objectives to simulate the applications where reliability cannot be compromised. Based on the results of simulation we show that the proposed approach has the capability to optimize all the objectives by maintaining a good value of reliability.

The paper is ordered as follows: Section 2 gives a brief review of the

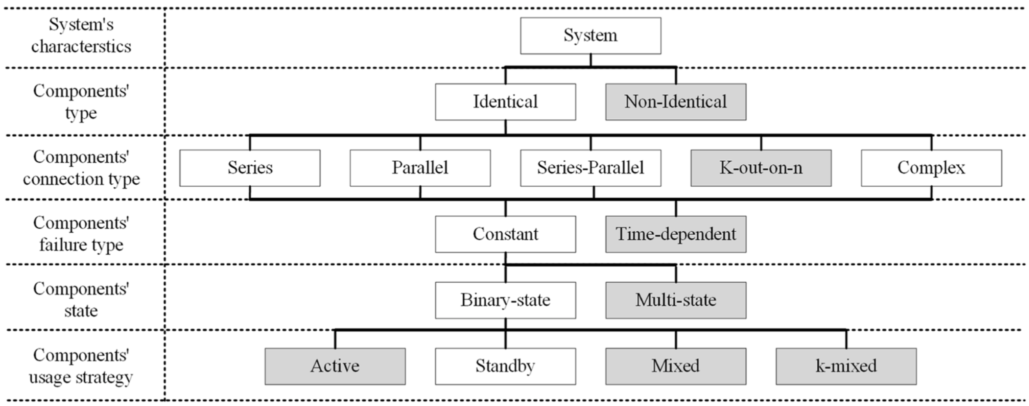

Fig. 1. Taxonomical depiction of the system configurations considered in this study (shaded ones).

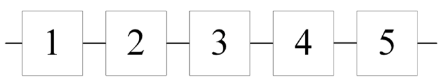

Fig. 2. Series system.

existing literature. Section 3 contains details of our proposed approach for many-objective formulations for RRAP. The step-by-step procedure is explained here. Section 4 provides the experimental results and the comparative analysis. Finally, Section 5 gives a concise conclusion of the work with future scopes. Also, Table 1 shows the notations and symbols used in this study.

2. Literature review

In this section, we briefly review the existing literature on (A) RRAP as a multi/many-objective optimization problem and (B) objective prioritization in the evolutionary optimization. Then at the end of the section, we highlight the novelty and major contributions of the current work in distinction to the existing works.

2.1. RRAP as a single objective optimization problem

RRAP was presented by Kuo and Prasad [21] with exhaustive study of the problem. The problem is inherently NP hard [22] and researchers worked on classical and meta-heuristic approaches to solve this problem. In Priravi et al. [23], a continuous-time Markov Chain model was developed for mixed and K-mixed strategies. The optimal structure of the multi-state series-parallel system is determined and solved using the discrete Bat algorithm in Xu et al. [24]. Zhang et al. [25] solved the reliability-based strength redundancy allocation problem using an Artificial bee colony algorithm. The maximum likely hood and uniformly minimum variance were used by Modibbo et al. [26] to estimate the system reliability. Sedghat and Abouei Ardakan [27] used a general strategy to improve system reliability. The computation of reliability was optimized using Markov based model in Guilani et al. [28]. A general network structure was proposed to solve series and parallel structure by Yeh et al. [29]. The Pareto solutions were calculated using the bound-rule-Bat algorithm for solving the redundancy allocation problem in Yeh [30]. In Ref. [31], the multi-objective redundancy allocation optimization was solved using a new evolutionary framework called multi-factorial evolutionary algorithm taking several real-life case studies. For k-out–of-n:G systems, a general reliability model based on a mixed redundancy strategy was proposed by Zhang et al. [32].

In Huang et al. [33], the survival signature heuristic was used to solve the RRAP. In Sharifi and Taghipour [34], multi-state components were considered as binary-state continuous performance level components. In Sharifi and Taghipour [35], the choice of allocating non-identical component and common cause failure of the component in multi-state series-parallel system was considered. A closed-form formula for calculating the reliability was used to model RAP in Sharifi et al. [36]. In Sharifi et al. [37], immune algorithm was used to solve the RRAP problem with multi-state failures. In Zhang et al. [38], a multi-graph was constructed to model the complex system, and it was solved using the factoring theorem-based algorithm.

2.2. RRAP as a multi/many-objective optimization problem

In Khalili-Damghani et al. [39], a decision support system was used to order performance according to the similarity to ideal solutions. In Garg et al. [40], PSO was used to solve multi-objective problem as single objective problem taking one objective at a time. To solve the RRAP, mean square error of the loss function was used in Salmasnia et al. [41]. In Kayedpour et al. [42], significance of time in RRAP was emphasised, where instantaneous availability, repairability and Markov chain were used to solve the problem. In Zaretalab et al. [43], optimization of more than one system with the choice of selecting suppliers was used to solve multi-objective availability-redundancy allocation problem. In Muhuri and Nath [44], bilevel formulation of RRAP was proposed for the multi-objective problem, and it was solved using a new evolutionary based approach. In Zhao et al. [45], the coarse-grained parallel genetic algorithm was used to solve the multi-objective model with rearrangement and replacement method. A binary matrix was used to model the multi-type production system for multi-objective RRAP in Wang et al. [46]. In Azimi and Asadi [47], maximization of reliability and minimize of total cost was performed using NSGA-II considering the optimal number of static synchronous compensator. A multi-objective model was formulated and solved using NSGA-II considering the mean time to failure and cost as objectives in Azizi and Mohammadi [48].

2.3. Objective prioritization in (evolutionary) optimization

In Brockhoff et al. [49], authors discussed whether all objectives are needed to be solved for an optimization problem. In Tan et al. [50], a goal sequence was used to perform multi-objective optimization and maintain priority. In Matsumoto et al. [51], objectives were distinguished as hard and soft, and are used to model the objective priority ranking strategy. Priority ranking for the objectives were considered for the virtual power plant, and used to formulate a multi-objective optimization problem in Gong et al. [52]. In Berrada et al. [53], priority among the objectives was used for nurse scheduling. In Aggelogiannaki et al. [54], prioritized multi-objective optimization with low computational cost was performed using simulated annealing. Li et al. [55] incorporated pre-emptive priority in a multi-objective optimization problem. Deb et al. [56], proposed a method to reduce the objectives using principal component analysis. They reduced the number of objectives to the most effective ones only. Also, in Pozo et al. [57], the

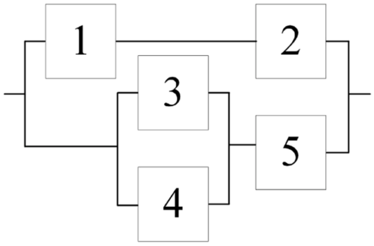

Fig. 3. Series-parallel system.

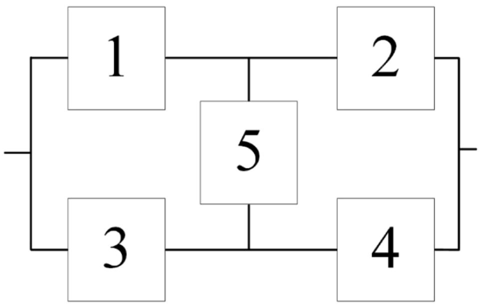

Fig. 4. Complex (bridge) system.

principal component analysis was used in multi-objective optimization for designing chemical supply chain. Goal programming was used to formulate off-grid systems by incorporating priority and decision maker information in Hussain et al. [58].

In contrast to the above, we may summarize the novelty and the major contributions of the current work as follows:

1. The paper proposes a novel formulation for the prioritized many-objective reliability redundancy allocation problems (PrMaORRAP) and introduce a customized evolutionary approach to solve the newly formulated problem.
2. The proposed formulation is unified in the evolutionary algorithmic framework through two separate algorithms. The whole formulation is transformed into a complete evolutionary process. To achieve the prioritized many-objective optimizations for RRAP, the optimization is divided into two separate modules: first is the main priority or the leader which stays at the top; and underneath the first, lie the second part in which rest of the objectives are optimized.
3. We demonstrate the working of the proposed PrMaORRAP considering four diverse system structure viz., the series system, series-parallel systems, complex bridge systems, and the overspeed gas turbine systems.
4. We perform a thorough comparative analysis in terms of the average solutions and the convergence, and show the efficacy of the proposed formulation.

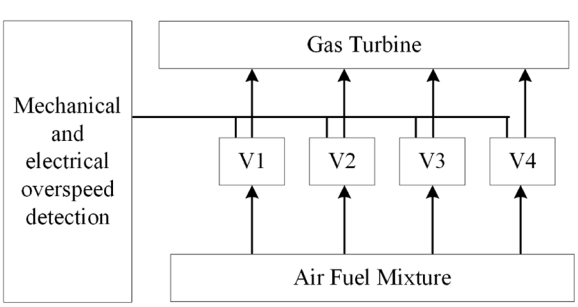

Fig. 5. Overspeed protection system of gas turbine.

The system configurations considered in this study are taxonomically shown in the Fig. 1 (shaded ones), similar to the ones provided in Refs. [36,59]. The system's strategy is standby for series, parallel, series-parallel or complex structure with identical binary-state constant failure rate.

3. Prioritized many-objective RRAP: formulation and solution

This section presents RRAP as prioritized many-objective problems and proposes a novel evolutionary based solution approach to solve it.

3.1. Formulation

Now, suppose, $R_S, C_S,\ W_S$ and V_S are the system reliability, system cost, system weight and system volume, respectively. With these notations, Eq. (1) shows the basic mathematical formulation of the many-objective RRAP.

$$\begin{aligned} &max\ R_s(r_i, n_i), min\ C_s(r_i, n_i), min\ W_s(n_i), min\ V_s(n_i) \\ &s.t.\ \ g(r_i, n_i) \le b,\ 0 \le r_i \le 1\ and\ 1 \le n_i \le m \end{aligned} \tag{1}$$

where, r is the component reliability, n is the number of components in a sub-system, and m is the number of sub-systems. The structure of the main function of the reliability changes based on the design of the system and the number of sub-systems. Three or more objectives depict the structure of many-objective optimization problems. By giving equal weightage to all the objectives, a complete system may hardly be constructed. One has to make choices to make a sustainable model. To handle this issue, we propose objective prioritized formulations to solve many-objective optimization problems.

In prioritized many-objective problems, objectives may have different priorities and may be optimized at different levels. That is, in prioritized many-objective optimization, based on the priorities, separate optimization levels viz., leader level and follower levels are used. The upper-level act as leader and the lower-levels acts as followers. This notion is transferred to the decision variables also which are upper and lower-level variables. The lower-level problems will be the constraints for the upper-level problem.

$$\begin{aligned} &L_1 : \min f_1(x), \\ &L_2 : \min f_2(x), \\ &\quad\vdots \\ &L_n : \min f_n(x), \\ &\quad s.t.x \in D \end{aligned} \tag{2}$$

where, n is the number of objectives, x is the decision variable, L are the priority levels and D is the decision space.

In RRAP, reliability is the crucial objective and the whole system depends upon it. If RRAP is solved purely as many-objective problem, then a significant amount of cost, weight and volume are saved but we may end up with an undesirable reliability. In order to make it as nearer to the optimal solutions as possible by simultaneously optimizing cost, weight and volume, we may formulate the problem as prioritized optimization problem considering reliability as the main objectives, and optimizing the rest under constraints. Thus, we formulate RRAP as an objective prioritized many-objective problem. To accommodate all the criteria and for obtaining the desirable value of reliability, we propose a novel method, named, 'prioritized many-objective optimization for RRAP'. Here, the upper-level problem maximizes the reliability, and the lower-level problem comprises aggregation of multiple optimization problems associated with the minimization of cost, weight, and volume. We formulate RRAP as a prioritized many-objective problem as follows:

$$\begin{aligned} &Max R_s(r_i, n_i), \\ &s.t. min\ C_s(r_i, n_i), min\ W_s(n_i), min\ V_s(n_i), g(r_i, n_i) \le b,\ 0 \le r_i \le 1\ and\ 1 \le n_i \le m \end{aligned} \tag{3}$$

Here, r is the reliability of the components, n is number of components in a sub-system, and m is the number of sub-systems. $R_S, C_S,\ W_S$

and V_S are system reliability, system cost, system weight and system volume, respectively.

The weighted sum approach is used to handle the lower-level objectives. The formulation used for the weighted sum approach is as follows:

$$\begin{aligned}&\min(w_1C_S + w_2W_S + w_3V_S)\\ &s.t.\ V_S - V \le 0, C_S - C \le 0, W_S - W \le 0,\ w_1 + w_2 + w_3 = 1\end{aligned} \tag{4}$$

Four different case studies (CSs) are studied here with different subsystems. These case studies are series systems (CS-1), series-parallel systems (CS-2), complex bridge system (CS-3), and overspeed protection system for gas turbine (CS-4) [60,61]. All the case studies are modeled in the structure of the prioritized many-objective model.

3.1.1. Series system

This is the simplest structure with all the sub-systems arranged in sequence. One typical series system is depicted in Fig. 2, where the number of sub-systems is five. The mathematical formulation of the prioritized many-objective model is a non-linear mixed-integer programming problem, as given below:

$$\begin{aligned}&Maxf\left(r^U, n^L\right) = \prod_{i=1}^{m} R_i(n_i)\\ &s.t. n \in \underset{n}{\operatorname{argmin}} \begin{cases} minC_s = \sum_{i=1}^{m} \alpha_i \left(-\frac{1000}{\ln(r_i)}\right)^{\beta_i} [n_i + \exp(0.25n_i)] \\ MinV_s = \sum_{i=1}^{m} w_i v_i^2 n_i^2 \\ minW_s = w_i n_i \exp(0.25n_i) \\ V_S - V \le 0, C_S - C \le 0, W_S - W \le 0 \end{cases}\\ &0 \le r_i \le 1, n_i \in \mathbb{Z}^+, 1 \le i \le m\end{aligned} \tag{5}$$

Here, $R_i(n_i) = 1 - (1 - r_i)^{n_i}$. Also, α_i and β_i represents the physical characteristics of the ith component. The argmin provides the value of n^L for which C_s, V_s and W_s are minimum for the selected r^U value. Here, the priorities among the objectives are imposed since the r^U is fixed for the argmin and it bounds n^L for the respective r^U value. This relationship will be followed in the objective also. Thus, the values of C_s, V_s and W_s are calculated for the selected r^U.

3.1.2. A series-parallel system

This system has sub-systems combined in series and parallel structure. Fig. 3 shows the structure of a series-parallel system. The nonlinear mixed integer mathematical formulation of series-parallel system as the prioritized many-objective model may be given as follows:

$$\begin{aligned}&Maxf\left(r^U, n^L\right) = 1 - (1 - R_1R_2)(1 - (R_3 + R_4 - R_3R_4)R_5)\\ &s.t. n \in \underset{n}{\operatorname{argmin}} \begin{cases} minC_s = \sum_{i=1}^{m} \alpha_i \left(-\frac{1000}{\ln(r_i)}\right)^{\beta_i} [n_i + \exp(0.25n_i)] \\ MinV_s = \sum_{i=1}^{m} w_i v_i^2 n_i^2 \\ minW_s = w_i n_i \exp(0.25n_i) \\ V_S - V \le 0, C_S - C \le 0, W_S - W \le 0 \end{cases}\\ &0 \le r_i \le 1, n_i \in \mathbb{Z}^+, 1 \le i \le m\end{aligned} \tag{6}$$

where, $R_i(n_i) = 1 - (1 - r_i)^{n_i}$. Also, α_i and β_i represents the physical characteristics of the ith component.

3.1.3. Complex (bridge) system

In complex (bridge) system, a bridge is there which joins the parallel system with a link. Due to this, the calculation of reliability is not straight forward but a complex function is formed. Accordingly, the mathematical formulation of the prioritized many-objective model for a complex (bridge) system can be expressed as follows:

$$\begin{aligned}&Maxf\left(r^U, n^L\right) = R_1R_2 + R_3R_4 + R_2R_4R_5 + R_2R_3R_5 - R_1R_2R_3R_4 - R_1R_2R_3R_5\\ &- R_1R_2R_4R_5 - R_1R_3R_4R_5 - R_2R_3R_4R_5 + 2R_1R_2R_3R_4R_5\\ &s.t. n \in \underset{n}{\operatorname{argmin}} \begin{cases} minC_s = \sum_{i=1}^{m} \alpha_i \left(-\frac{1000}{\ln(r_i)}\right)^{\beta_i} [n_i + \exp(0.25n_i)] \\ MinV_s = \sum_{i=1}^{m} w_i v_i^2 n_i^2 \\ minW_s = w_i n_i \exp(0.25n_i) \\ V_S - V \le 0, C_S - C \le 0, W_S - W \le 0 \end{cases}\\ &0 \le r_i \le 1, n_i \in \mathbb{Z}^+, 1 \le i \le m\end{aligned} \tag{7}$$

where, $R_i(n_i) = 1 - (1 - r_i)^{n_i}$. Also, α_i and β_i represents the physical characteristics of the ith component. A typical complex (bridge) system is shown in the Fig. 4.

3.1.4. Overspeed protection system for gas turbine

The overspeed protection system for gas turbine is shown in Fig. 5. The system is used for controlling the overspeed of the turbine with the help of valves which provide fuel. The mathematical formulation of the prioritized many-objective model for an overspeed protection system for gas turbine can be expressed as follows:

$$\begin{aligned}&Maxf\left(r^U, n^L\right) = \prod_{i=1}^{m} [1 - (1 - r_i)^{n_i}]\\ &s.t. n \in \underset{n}{\operatorname{argmin}} \begin{cases} minC_s = \sum_{i=1}^{m} \alpha_i \left(-\frac{1000}{\ln(r_i)}\right)^{\beta_i} [n_i + \exp(0.25n_i)] \\ MinV_s = \sum_{i=1}^{m} w_i v_i^2 n_i^2 \\ minW_s = w_i n_i \exp(0.25n_i) \\ V_S - V \le 0, C_S - C \le 0, W_S - W \le 0 \end{cases}\\ &0 \le r_i \le 1, n_i \in \mathbb{Z}^+, 1 \le i \le m\end{aligned} \tag{8}$$

where, $C(r_i) = \alpha_i\left(-\frac{T}{\ln(r_i)}\right)^{\beta_i}$. Also, α_i and β_i represents the physical characteristics of the ith component. Further, T is the operating time during which the components must not fail.

3.2. Proposed solution approach

While optimizing all the objectives of RRAP using pure multi-objective solutions, we obtain solutions which are optimal in all objectives equally [2,18]. But in real-life applications, this is often not possible [19]. To make the system viable, there requires priorities among the objectives. For example, the main criterion of the industrial application such as network, manufacturing and safety system in transport is throughput, costs, or reliability [15,16,44,62]. Additionally, there are implications like space scarcity etc. To accommodate these challenges, our proposed approach attempts to solve the problem of reliability (which is the main criteria here) as a prime objective and

Algorithm 1
Prioritized many-objective optimization for RRAP.

Input: Case study type (type of case study and the number of sub-systems).
Output: Optimal combination of component reliability and number of components.
1: Initial population: P_t which contain randomly generated component reliability r_i.
2: Fitness calculation (reliability, cost, weight and volume) of the candidate solutions.

- Call n_i = Lower-level optimization function (m, r_i).
- Calculate the fitness value of reliability based upon the provided n_i and r_i values. Cost, weight and volume are also recorded.

3: Execute the genetic algorithm:

- Apply tournament selection to select the solution for further process.
- Recombination.
- Call n_i = Lower-level optimization function (m, r_i) for newly generated r_i.
- Calculate the fitness value of reliability based upon the provided n_i and r_i values. Cost, weight and volume are also recorded.
- Select new solutions with optimal fitness to form new population.

4: Go to Step 3 until termination criteria.

Algorithm 2
Lower-level optimization function.

Input: Number of sub-systems (m) and component reliability (r_i).
Output: A set of near optimal solutions from the population.
1: Initial Population: Randomly generate a set of initial solutions P_t which contain randomly generated number of components n_i.
2: Calculate the values of cost, weight and volume based upon the provided n_i and r_i values.
3: Normalize the values of cost, weight and volume. A scalar function combining all three is formed with uniformly generated weight vectors. The value provided by the scalar function is considered as fitness value.
5: Truncate the population to the original size by selecting the best individuals.
6: Apply tournament selection to select the solution from the population.
7: Generate new solution using recombination.
8: Append new and old individuals in one population.
9: Go to step 2 until termination criteria.

$$\overbrace{0.78 \quad 0.89 \quad 0.87 \quad 0.75 \quad 0.70}^{r_i}$$

Fig. 6. Randomly generated solution for upper-level.

considers the additional objectives such as cost, weight, and volume as secondary objectives. So, we develop a customized evolutionary approach for this problem. The proposed formulation is unified in the evolutionary algorithmic framework, and hence transformed into a complete evolutionary process, as shown in Algorithms 1 and 2. To achieve the prioritized many-objective optimization for RRAP, the optimization is divided into two modules. One is the main priority or the leader which will stay at the top level. Underneath the first lie the second part in which rest of the objectives are optimized. The whole procedure can be characterized in initialization, fitness calculation, lower-level module, recombination and termination which are briefly explained next.

$$\overbrace{3\ 3\ 3\ 2\ 2}^{n_i}$$

Fig. 8. Randomly generated solution for lower-level.

3.2.1. *Initial population*

A randomly generated set of prospective solutions of size N is used as initial population. In our prioritized many-objective model, the decision variable for the upper-level is component reliability (r_i), as may be seen in Fig. 6. This figure also shows a sample randomly generated solution.

3.2.2. *Fitness calculation*

The objective function used to calculate the fitness values of all the solutions of population. Here in our problem, the objective functions are system reliability, cost, weight and volume. But, in this step, only reliability value is computed. The considered upper-level variable is r_i, using which the lower-level objectives: cost, weight and volume are computed. For a particular value of component reliability, optimal values of cost, weight and volume are calculated in the lower-level. By using the value of corresponding lower-level variable (n_i), the value of system reliability is computed.

3.2.3. *Recombination (selection, crossover and mutation)*

We have used the tournament selection to select the solution for crossover and mutation in our approach. A tournament is done among two randomly selected solutions and the better one is used for the crossover and mutation.

In our approach, the solution structure comprises two different types of decision variables (Fig. 7). First one is the reliability of the components which is real-valued, and the second one is the number of redundant components which is integer-valued (Fig. 8). For such solution structure, blend crossover (BLX) is used. In this crossover, there are two parents, which are: r_i^1/n_i^1 and r_i^2/n_i^2. Using these, an interval is created with the range $[r_i^1/n_i^1 - \alpha(r_i^2/n_i^2 - r_i^1/n_i^1), r_i^2/n_i^2 + \alpha(r_i^2/n_i^2 - r_i^1/n_i^1)]$, where α provide the outside range area provided by the user. From this interval and the defined outside area, randomly a value is selected which forms the new solution. Fig. 9 shows the BLX operator with its inside and outside range.

A typical crossover operation is shown in the Fig. 10(a). For mutation, normal distributed mutation operator is used. The mathematical description of the operator is given in Eq. (9). Mutation operation example is shown in Fig. 10(b).

$$r_i'/n_i' = r_i/n_i + N(0,1) \tag{9}$$

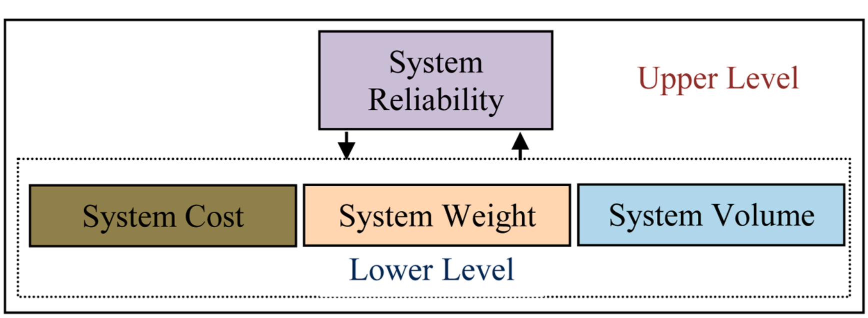

Fig. 7. Upper-level and lower-level objectives.

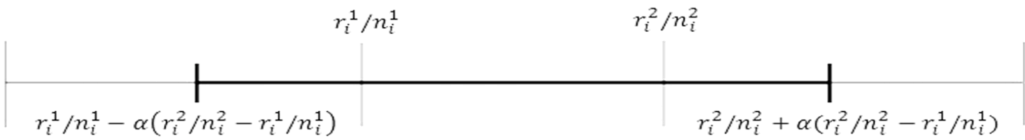

Fig. 9. Blend crossover range.

Parent 1	0.4936	0.0961	0.8099	0.3954	3	3	3	4
Parent 2	0.8430	0.6620	0.9610	0.5978	5	2	2	2
Child 1	0.8409	0.3417	0.8007	0.4324	4	3	3	3
Child 2	0.4958	0.4164	0.9704	0.5609	4	2	2	3

(a)

Parent	0.8623	0.7475	0.6675	0.9317	3	3	2	5
Child	0.6807	0.7423	0.5209	0.5824	3	3	2	5

(b)

Fig. 10. (a) Sample crossover example and (b) Sample mutation example.

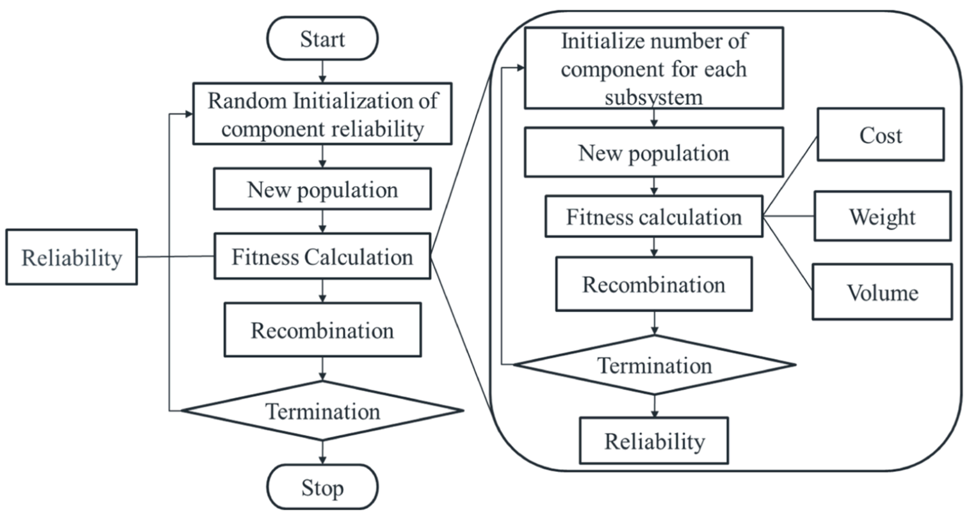

Fig. 11. Prioritized many-objective optimization for RRAP.

3.2.4. *Termination*

After a certain set of iterations of the previous steps, the whole procedure will terminate giving the optimized values for the RRAP. All the steps of the proposed PrMaORRAP are shown in the Fig. 11.

4. Simulation results

This section presents the details of the conducted experiments for solving the prioritized many-objective optimization for RRAP formulated in the Section 3. For the simulation, we have used a licensed Matlab 2018a software on a machine with a 4 GB RAM and an Intel(R) Core(TM) i5-2400 CPU to conduct our experiments. To have a comparative view of the results, we have compared the results with previously solved solutions of the problems. First, we have discussed about the datasets employed for our experimentation.

Table 2
Data used in the series-parallel system.

i	$10^5\alpha_i$	β_i	$W_i v_i^2$	w_i	V	C	W
1	2.5	1.5	2	3.5	180	175	100
2	1.45	1.5	4	4			
3	0.541	1.5	5	4			
4	0.541	1.5	8	3			
5	2.1	1.5	4	4.5			

4.1. *Data sets*

Table 3
Data used in the complex (bridge) system and the series system.

i	$10^5\alpha_i$	β_i	$W_i v_i^2$	w_i	V	C	W
1	2.33	1.5	1	7	110	175	200
2	1.45	1.5	2	8			
3	0.541	1.5	3	8			
4	8.05	1.5	4	6			
5	1.95	1.5	2	9			

Table 2 provides the data for the CS-1 with five sub-systems. Table 3 shows the data for CS-2 and CS-3 with five sub-systems each, whereas Table 4 shows the input data for the overspeed drive system of CS-4 with four sub-systems.

Table 4
Data used in the overspeed drive system systems.

i	$10^5\alpha_i$	β_i	v_i	w_i	V	C	W	T
1	1	1.5	1	6	250	400	500	1000h
2	2.3	1.5	2	6				
3	0.3	1.5	3	8				
4	2.3	1.5	2	7				

Table 5
Average solutions for CS-1.

Iteration	250	500	1000	2000	4000	5000	8000	10,000	15,000	20,000
Reliability	0.9998	0.9998	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999
Cost	172.9	171.7	169.5	171.5	173.0	174.3	173.9	173.9	173.7	174.4
Weight	194.6	195.7	195.7	195.7	195.7	195.7	195.7	195.7	195.7	195.7
Volume	88	87	92	92	92	92	92	92	92	92
Time	7053	14,078	28,130	56,226	112,441	140,556	224,894	281,096	421,590	562,051

Table 6
Average solutions for CS-2.

Iteration	250	500	1000	2000	4000	5000	8000	10,000	15,000	20,000
Reliability	0.9197	0.9215	0.9234	0.9237	0.9266	0.9273	0.9291	0.9293	0.9298	0.9300
Cost	170.0	174.4	174.1	173.8	172.5	174.3	174.4	174.8	174.9	175.0
Weight	190.4	191.5	190.4	190.4	191.5	191.5	191.5	191.5	191.5	191.5
Volume	85	85	85	85	83	83	83	83	83	83
Time	3135	6258	12,504	24,996	49,978	62,470	99,936	124,913	187,355	249,795

4.2. Simulation results using prioritized many-objective optimization for RRAP

The simulation is performed for 20 independent runs. We have first shown the convergence pattern obtained using the proposed formulation. Then, we compare the best solutions with decision and objective values with the previously known results of the problem. The average results for all the objectives are presented in Tables 5–8 for all the case studies. The convergence graphs of CS-1 displaying reliability, cost, weight and volume are shown in Fig. 12.

Similarly, Figs. 13–15 are showing the convergence graphs for CS-2, CS-3 and CS-4 respectively. As may be seen in Fig. 12(a), reliability is improving throughout the span of iterations. In Fig. 12(b), cost first start improving, and then it goes back. In Fig. 12(c) and (d), weight and volume are not improving compared to the previous values; but, for a particular reliability value, cost, volume, and weight are optimized.

For CS-2, as may be seen in Fig. 13(a), reliability is improving. Cost and weight followed mixed pattern as may be seen in Fig. 13(b) and (c), respectively. In Fig. 13(d), volume is improved. In Fig. 14(a) and (b), reliability and cost are improved throughout. Weight and volume stayed constant in Fig. 14(c) and (d). In Fig. 15(a) reliability is improving throughout. Cost, weight and volume followed mixed pattern as can be seen in Fig. 15(b)–(d). In Fig. 15(b)–(d), cost, weight and volume are not improving when compared with the existing values. But for specific reliability values, cost, volume and weight are optimized.

From the Figs. 12–15, we may observe the convergence of the reliability, cost, weight and volume plots. In all these figures, we can see that reliability has improved throughout, but other objectives have not improved that much. This happened due to the priority relationships among the reliability, cost, weight, and volume. All the objectives are optimized but the conflicting nature of the objectives are limiting the improvements of the cost, weight, and volume.

4.3. Comparison with existing results

Here, we compare the results obtained from the proposed formulation with the previously known results from the literature [60,61, 63–77]. In Table 9, the first row shows the works with which results are compared. In the second row, the best function value of reliability is compared. After that, in rows 3 to 7, values of the decision variable n_i is given which provide the number of components used for ith sub-system. Then, the next five rows (which is r_i), show the component reliability for the ith sub-system. At the end, the last three rows show the saved quantity of volume, cost and weight. In Table 9, results obtained from the CS- 1 are compared with the existing results from the literature. Here, we can see that the proposed approach is performing well in terms of reliability. Additionally, the proposed approach is also able to save volume, cost, and weight. Table 10 gives the results of CS-2, from which it can be seen that results given by the proposed approach are comparable with the same of the other existing methods in terms of reliability, cost, weight and volume altogether.

In Table 11, results obtained for CS-3 are compared with the results given by other competitive methods. It is clearly visible that reliability obtained from the proposed approach is the best. In Table 12, results obtained for CS-4 are compared with existing results. Here, we have observed comparable values of reliability as well as the best value of cost for the proposed approach.

Table 7
Average solutions for CS-3.

Iteration	250	500	1000	2000	4000	5000	8000	10,000	15,000	20,000
Reliability	0.99997	0.99998	0.99998	0.99998	0.99998	0.99998	0.99998	0.99998	0.99998	0.99998
Cost	170.5	171.7	173.2	174.7	174.7	174.8	174.9	174.9	175.0	175.0
Weight	99.3	99.3	99.3	99.3	99.3	99.3	99.3	99.3	99.3	99.3
Volume	142	142	142	142	142	142	142	142	142	142
Time	3136	6259	12,505	25,000	49,989	62,484	99,968	124,957	187,433	249,907

Table 8
Average solutions for CS-4.

Iteration	250	500	1000	2000	4000	5000	8000	10,000	15,000	20,000
Reliability	0.9989	0.9996	0.9998	0.9998	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999
Cost	303.7	276.8	384.2	377.9	392.5	392.5	392.5	384.0	384.0	384.0
Weight	321.8	439.0	439.0	499.4	484.6	484.6	484.6	484.6	484.6	484.6
Volume	133	163	163	194	195	195	195	195	195	195
Time	3203	6111	11,887	23,644	47,245	58,962	94,312	118,003	177,165	238,006

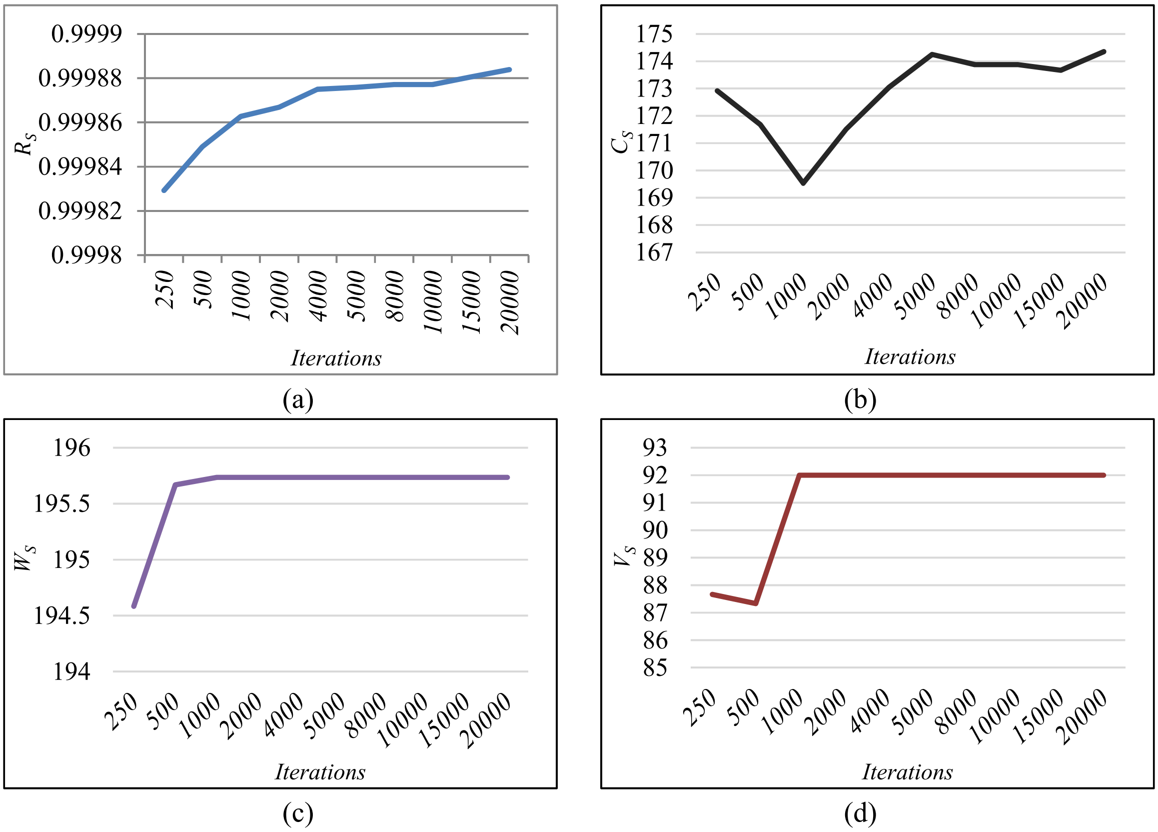

Fig. 12. Convergence graph: (a) Reliability, (b) Cost, (c) Weight and (d) Volume for CS-1.

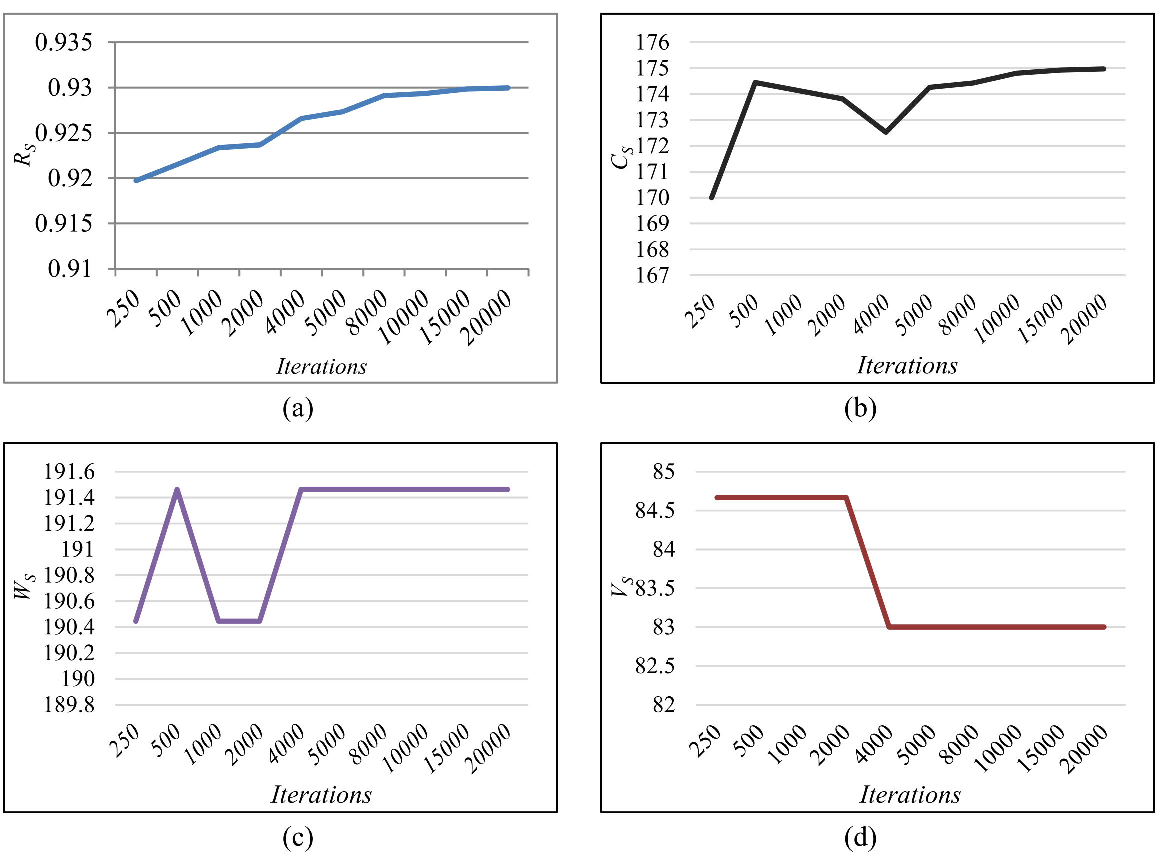

Fig. 13. Convergence graphs: (a) Reliability, (b) Cost, (c) Weight and (d) Volume for CS-2.

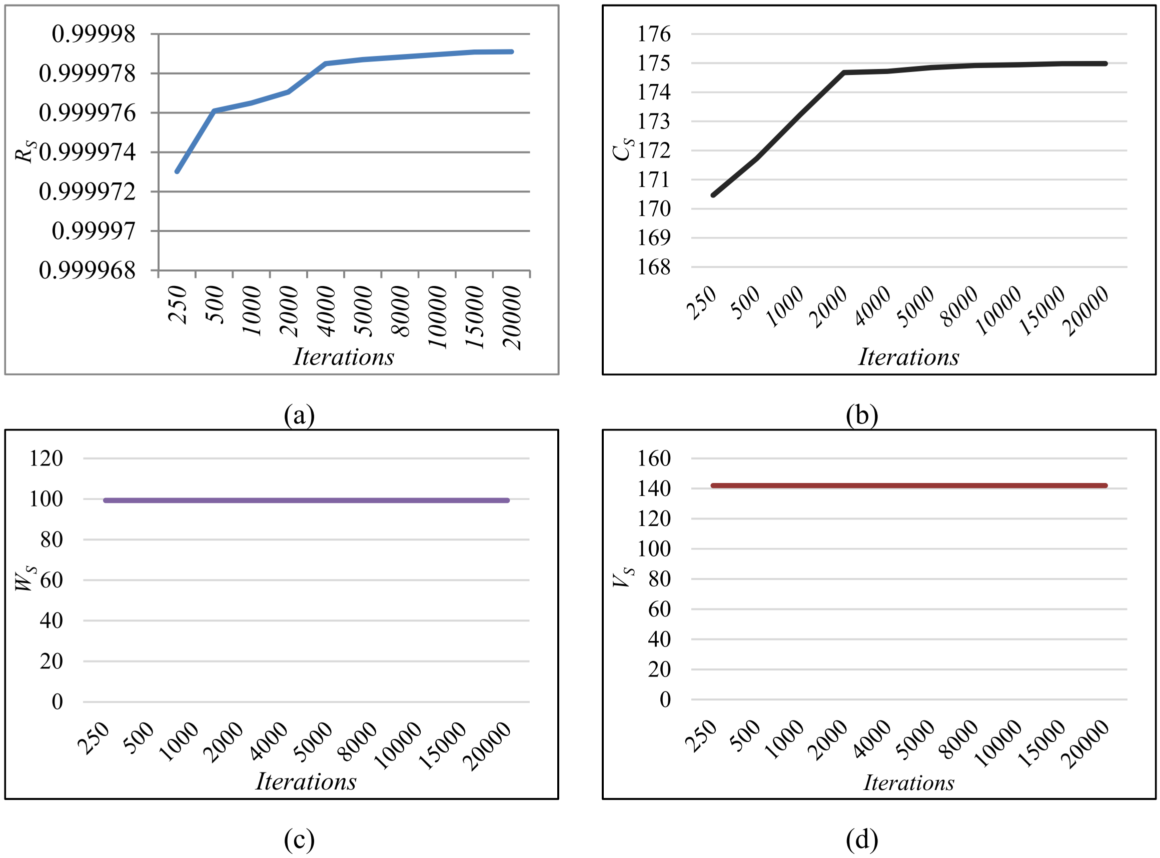

Fig. 14. Convergence graphs: (a) Reliability, (b) Cost, (c) Weight and (d) Volume for CS-3.

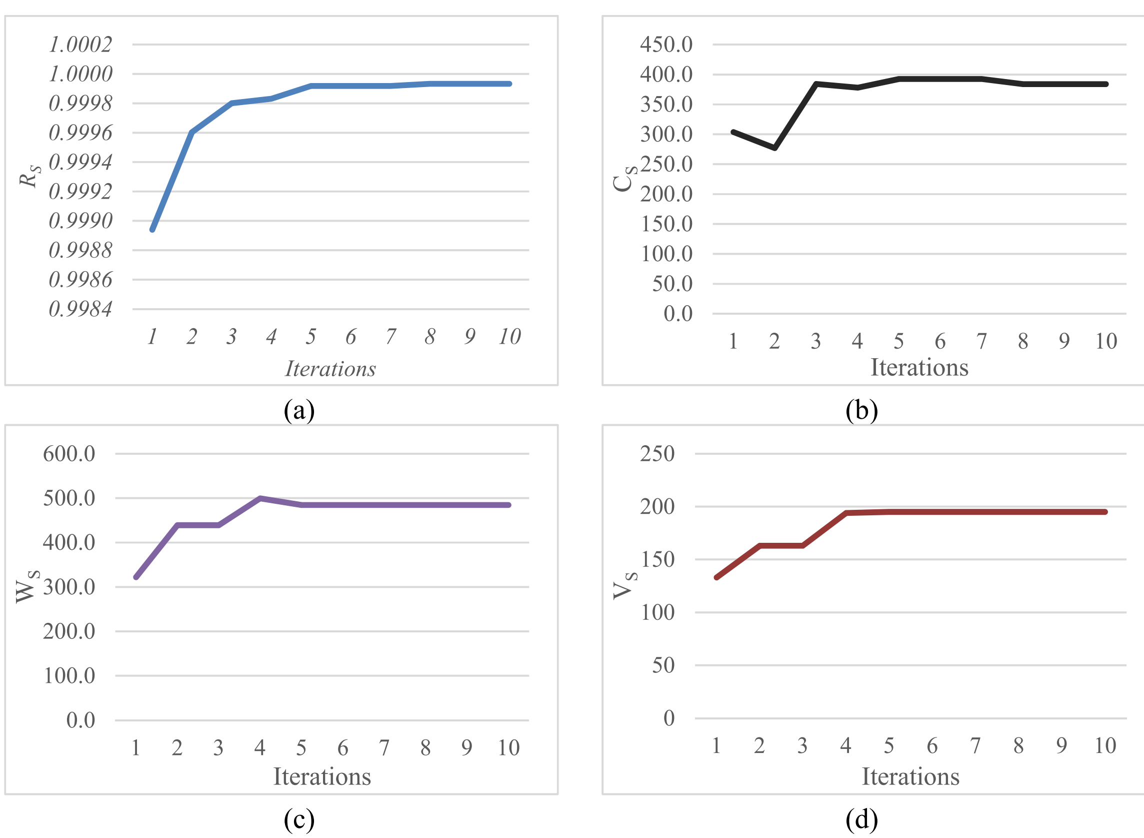

Fig. 15. Convergence graphs: (a) Reliability, (b) Cost, (c) Weight and (d) Volume for CS-4.

Table 9
Comparing the results of PrMaORRAP for CS-1 with previous results from literature.

	Wu et al. (2011)	Hseih and You 2011	Wang and Li 2012	Valian et al. (2013)	Afonso 2013	Kanagaraj 2013	Ardakan and Hamadani (2014)	Liu and Qin 2014	He 2015	Garg 2015b	Huang 2015	Liu 2016	Mellal and Zio 2016	Kim and Kim 2017	Ouyang et al. 2019	Juybari et al. 2019	Li 2022	Proposed Approach
$f(r,n)$	0.99989	0.99989	0.99988	0.99989	0.99980	0.99989	0.99997	0.99989	0.99989	0.99989	0.99989	0.99989	0.99989	0.99999	0.99989	0.99998	0.99998	0.99989
n_1	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
n_2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
n_3	2	2	2	2	2	2	3	2	2	2	2	2	2	2	2	2	2	3
n_4	4	4	4	4	4	4	3	4	4	4	4	4	4	4	4	4	4	3
n_5	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
r_1	0.8287	0.8166	0.8281	0.8281	0.8276	0.8281	0.8045	0.8280	0.8283	0.8281	0.8278	0.8281	0.8281	0.8289	0.8281	0.8191	0.8198	0.8076
r_2	0.8580	0.8687	0.8578	0.8580	0.8574	0.8578	0.8571	0.8578	0.8580	0.8580	0.8577	0.8578	0.8578	0.8571	0.8578	0.8550	0.8590	0.8635
r_3	0.9136	0.8587	0.9142	0.9142	0.9141	0.9142	0.8673	0.9142	0.9142	0.9141	0.9144	0.9142	0.9142	0.9285	0.9142	0.9338	0.9331	0.8736
r_4	0.6480	0.7102	0.6480	0.6479	0.6492	0.6481	0.7275	0.6481	0.6478	0.6480	0.6486	0.6481	0.6480	0.6153	0.6480	0.6140	0.6090	0.7241
r_5	0.7023	0.7534	0.7041	0.7046	0.7040	0.7042	0.7641	0.7040	0.7042	0.7042	0.7029	0.7042	0.7042	0.7365	0.7036	0.7589	0.7566	0.6943
V	5	18	5	5	5	5	18	5	5	5	–	5	5	5	–	5	5	18
C	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0001	0.0000	0.0000	0.0001	–	0.0000	0.0000	0.0000	–	0.0004	0.0000	0.1155
W	1.5605	4.2648	1.5605	1.5605	1.5605	1.5605	4.2648	1.5605	1.5605	1.5605	–	1.5605	1.5605	1.5605	–	1.5605	1.5605	4.2648

Table 10
Comparing the results of PrMaORRAP for CS-2 with existing results from literature.

	Wu et al. (2011)	Hseih and You 2011	Valian et al. (2013)	Afonso 2013	Kanagaraj 2013	Ardakan and Hamadani (2014)	Liu and Qin 2014	He 2015	Garg 2015b	Huang 2015	Liu 2016	Mellal and Zio 2016	Kim and Kim 2017	Ouyang et al. 2019	Juybari et al. 2019	Li 2022	Proposed Approach
$f(r,n)$	0.93168	0.93168	0.93168	0.93168	0.93168	0.96958	0.93168	0.93168	0.93168	0.93168	0.93168	0.93168	0.97401	0.93168	0.96958	0.96959	0.93117
n_1	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
n_2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
n_3	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
n_4	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
n_5	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
r_1	0.7804	0.7794	0.7794	0.7799	0.7794	0.7646	0.7794	0.7794	0.7794	0.7795	0.7794	0.7794	0.7642	0.7794	0.7665	0.7848	0.7899
r_2	0.8718	0.8718	0.8718	0.8721	0.8718	0.8875	0.8718	0.8718	0.8718	0.8717	0.8718	0.8572	0.8887	0.8718	0.8876	0.8889	0.8646
r_3	0.9024	0.9029	0.9029	0.9034	0.9029	0.9154	0.9029	0.9029	0.9029	0.9028	0.9029	0.9029	0.9160	0.9029	0.9153	0.9156	0.8981
r_4	0.7115	0.7114	0.7114	0.7110	0.7114	0.6935	0.7114	0.7114	0.7114	0.7115	0.7114	0.7114	0.6933	0.7114	0.6957	0.6916	0.7108
r_5	0.7874	0.7878	0.7878	0.7869	0.7878	0.7760	0.7878	0.7878	0.7878	0.7878	0.7878	0.7878	0.7717	0.7879	0.7758	0.7744	0.7958
V	27	27	27	27	27	27	27	27	27	27	–	27	27	–	27	27	27
C	0.1215	–	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	–	0.0000	0.0000	0.0001	–	0.0002	0.0000	0.0399
W	7.5189	7.5189	7.5189	7.5189	7.5189	7.5189	7.5189	7.5189	7.5189	–	7.5189	7.5189	7.5189	–	7.5189	7.5189	7.5189

Table 11
Comparing the results of PrMaORRAP for CS-3 with existing results from literature.

	Wu et al. (2011)	Hseih and You 2011	Wang and Li 2012	Valian et al. (2013)	Afonso 2013	Kanagaraj 2013	Ardakan and Hamadani (2014)	Liu and Qin 2014	He 2015	Garg 2015b	Huang 2015	Liu 2016	Mellal and Zio 2016	Kim and Kim 2017	Ouyang et al. 2019	Juybari et al. 2019	Li 2022	Proposed Approach
$f(r,n)$	0.99998	0.99998	0.99998	0.99998	0.99998	0.99998	0.99999	0.99998	0.99998	0.99998	0.99998	0.99998	0.99998	0.99999	0.99998	0.99999	0.99999	0.99998
n_1	2	2	2	2	2	2	3	2	2	2	2	2	2	3	2	3	3	3
n_2	2	2	2	2	2	2	3	2	2	2	2	2	2	3	2	3	3	3
n_3	2	2	2	2	2	2	2	2	2	2	2	2	2	1	2	1	1	2
n_4	2	2	2	2	2	2	1	2	2	2	2	2	2	2	2	2	2	2
n_5	4	4	4	4	4	4	3	4	4	4	4	4	4	3	4	3	3	3
r_1	0.8192	0.8196	0.8196	0.8199	0.8220	0.8197	0.8248	0.8197	0.8457	0.8197	0.8446	0.8450	0.8197	0.8263	0.8198	0.8254	0.8224	0.8218
r_2	0.8437	0.8450	0.9450	0.8453	0.8437	0.8450	0.8428	0.8450	0.8457	0.8449	0.8446	0.8450	0.8450	0.8487	0.8450	0.8479	0.8224	0.8466
r_3	0.8947	0.8954	0.8955	0.8955	0.8913	0.8955	0.9082	0.8955	0.8949	0.8955	0.8953	0.8955	0.8955	0.8980	0.8957	0.8985	0.8445	0.8647
r_4	0.8954	0.8955	0.8955	0.8954	0.8987	0.8955	0.8970	0.8955	0.8959	0.8955	0.8958	0.8955	0.8955	0.9119	0.8953	0.9093	0.9015	0.8514
r_5	0.8691	0.8685	0.8685	0.8683	0.8682	0.8684	0.8655	0.8684	0.8683	0.8685	0.8685	0.8684	0.8684	0.8596	0.8684	0.8620	0.9105	0.8786
V	40	40	40	40	40	40	62	–	40	40	40	62	–	53	–	53	53	38
C	0.0006	0.0000	0.0000	0.0000	0.0004	0.0000	0.0001	0.0000	0.0000	0.0000	–	0.0000	–	0.0000	–	0.0016	0.0000	0.0000
W	1.6093	1.6093	1.6093	1.6093	1.6093	1.6093	6.1041	1.6093	1.6093	1.6029	–	1.6093	1.6093	7.1108	–	7.1108	7.1108	0.7059

Table 12
Comparing the results of PrMaORRAP for CS-4 with previous results from literature.

	Wu et al. (2011)	Hseih and You 2011	Wang and Li 2012	Valian et al. (2013)	Afonso 2013	Kanagaraj 2013	Liu and Qin 2014	He 2015	Garg 2015b	Huang 2015	Mellal and Zio 2016	Proposed Approach
$f(r,n)$	0.99996	0.99995	0.99996	0.99996	0.99995	0.99995	0.99995	0.99995	0.99995	0.99995	0.99995	0.99993
n_1	5	5	5	5	5	5	5	5	5	5	5	5
n_2	6	5	6	5	6	5	6	6	5	5	6	5
n_3	4	4	4	4	4	4	4	4	4	4	4	4
n_4	5	6	5	6	5	6	5	5	6	6	5	6
r_1	0.9016	0.9016	0.9016	0.9016	0.9015	0.9016	0.9016	0.9016	0.9016	0.9017	0.9016	0.9140
r_2	0.8500	0.8882	0.8499	0.8882	0.8500	0.8882	0.8499	0.8499	0.8882	0.8882	0.8499	0.8911
r_3	0.9482	0.9482	0.9481	0.9481	0.9481	0.9481	0.9481	0.9481	0.9482	0.9482	0.9481	0.9352
r_4	0.8881	0.8500	0.8882	0.8499	0.8882	0.8499	0.8882	0.8882	0.8500	0.8499	0.8882	0.8244
V	55	55	55	55	55	55	55	55	55	–	55	55
C	0.0000	0.0001	0.0000	0.0000	0.0021	0.0000	0.0000	0.0000	0.0003	–	0.0000	16.0478
W	24.0819	15.3635	24.8019	15.3635	24.8019	15.3635	24.8019	24.8020	15.3635	–	24.8019	15.3635

5. Conclusion

In this paper, we have reported a study of the RRAP as a prioritized many-objective optimization problem considering all the four objectives: system reliability, system cost, weight and volume. All the objectives are considered simultaneously but reliability got the priority over others. Thus, we have formulated the prioritized many-objective RRAP (PrMaORRAP) for four different system structures viz., series, series-parallel systems, complex bridge systems, and overspeed gas turbine system. Then, for the formulated PrMaORRAPs, we have provided a novel solution procedure based on the well-known GA. We have demonstrated its working step by step, and detailed discussions are provided. We have presented all the results in a competitive fashion to have a thorough comparative assessment of the proposed approach. Furthermore, we have compared the results obtained from the proposed approach with the approaches available in the literature. From the experimental results, it is observed that the proposed approach is superior to others for most of the time. It has the capability to optimize all the objectives by maintaining a good value of reliability. Future research may consider solving the MaORRAPs with more than four objectives considering more complex systems and additional objectives such as fault-tolerance, thermal stability, and energy efficiency.

Author statement

During the preparation of this work the authors have not used generative AI and AI-assisted technologies.

CRediT authorship contribution statement

Rahul Nath: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Pranab K. Muhuri:** Writing – review & editing, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

Authors expresses their sincere gratitude and thankfulness to the learned editors and the reviewers for all of their valuable comments, which played a significant role while revising the manuscript, and in improving its overall technical quality. Authors are also grateful to the South Asian University, New Delhi, India for providing excellent infrastructural support through their Computational Intelligence Lab while carrying out this research.

References

[1] Deb K, Jain H. An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, part I: solving problems with box constraints. IEEE Trans Evol Comput 2013;18(4):577–601.
[2] Deb K. Multi-objective optimization using evolutionary algorithms, 16. John Wiley & Sons; 2001.
[3] Li B, Li J, Tang K, Yao X. Many-objective evolutionary algorithms: a survey. ACM Comput Surv (CSUR) 2015;48(1):1–35.
[4] Sato H, Aguirre HE, Tanaka K. Pareto partial dominance MOEA and hybrid archiving strategy included CDAS in many-objective optimization. In: Proceedings of the IEEE congress on evolutionary computation. IEEE; 2010. p. 1–8.
[5] Hadka D, Reed P. Borg: an auto-adaptive many-objective evolutionary computing framework. Evol Comput 2013;21(2):231–59.
[6] He Z, Yen GG, Zhang J. Fuzzy-based Pareto optimality for many-objective evolutionary algorithms. IEEE Trans Evol Comput 2013;18(2):269–85.
[7] Ishibuchi H, Akedo N, Nojima Y. Behavior of multiobjective evolutionary algorithms on many-objective knapsack problems. IEEE Trans Evol Comput 2014; 19(2):264–83.
[8] Zhou A, Zhang Q. Are all the subproblems equally important? Resource allocation in decomposition-based multiobjective evolutionary algorithms. IEEE Trans Evol Comput 2015;20(1):52–64.
[9] Bader J, Zitzler E. HypE: an algorithm for fast hypervolume-based many-objective optimization. Evol Comput 2011;19(1):45–76.
[10] He X, Zhou Y, Chen Z. An evolution path-based reproduction operator for many-objective optimization. IEEE Trans Evol Comput 2017;23(1):29–43.
[11] Jiang S, Yang S. A strength Pareto evolutionary algorithm based on reference direction for multiobjective and many-objective optimization. IEEE Trans Evol Comput 2017;21(3):329–46.
[12] Xiang Yi, Zhou Y, Li M, Chen Z. A vector angle-based evolutionary algorithm for unconstrained many-objective optimization. IEEE Trans Evol Comput 2016;21(1): 131–52.
[13] Zhang X, Tian Y, Jin Y. A knee point-driven evolutionary algorithm for many-objective optimization. IEEE Trans Evol Comput 2014;19(6):761–76.
[14] Cao B, Wang X, Zhang W, Song H, Lv Z. A many-objective optimization model of industrial internet of things based on private blockchain. IEEE Netw 2020;34(5): 78–83.
[15] Zhang Z, Cao Y, Cui Z, Zhang W, Chen J. A many-objective optimization based intelligent intrusion detection algorithm for enhancing security of vehicular networks in 6G. IEEE Trans Veh Technol 2021;70(6):5234–43.
[16] Mnasri S, Nasri N, Van den Bossche A, Val T. Improved many-objective optimization algorithms for the 3D indoor deployment problem. Arab J Sci Eng 2019;44:3883–904.
[17] Nath R, Muhuri PK. Evolutionary optimization based solution approaches for many objective reliability-redundancy allocation problem. Reliab Eng Syst Saf 2022;220: 108190.
[18] Wang R. Preference-inspired co-evolutionary algorithms. University of Sheffield; 2013.
[19] Cohon JL. Multicriteria programming: brief review and application. Des Optim 1985:163–91.
[20] Thiele L, Miettinen K, Korhonen PJ, Molina J. A preference-based evolutionary algorithm for multi-objective optimization. Evol Comput 2009;17(3):411–36.
[21] Kuo W, Prasad VR. An annotated overview of system-reliability optimization. IEEE Trans Reliab 2000;49(2):176–87.
[22] Chern MS. On the computational complexity of reliability redundancy allocation in a series system. Oper Res Lett 1992;11(5):309–15.
[23] Peiravi A, Nourelfath M, Zanjani MK. Redundancy strategies assessment and optimization of k-out-of-n systems based on Markov chains and genetic algorithms. Reliab Eng Syst Saf 2022;221:108277.
[24] Xu Y, Pi D, Yang S, Chen Y. A novel discrete bat algorithm for heterogeneous redundancy allocation of multi-state systems subject to probabilistic common-cause failure. Reliab Eng Syst Saf 2021;208:107338.
[25] Zhang J, Li L, Chen Z. Strength–redundancy allocation problem using artificial bee colony algorithm for multi-state systems. Reliab Eng Syst Saf 2021;209:107494.
[26] Modibbo UM, Arshad M, Abdalghani O, Ali I. Optimization and estimation in system reliability allocation problem. Reliab Eng Syst Saf 2021;212:107620.
[27] Sedaghat N, Abouei Ardakan M. G-mixed: a new strategy for redundant components in reliability optimization problems. Reliab Eng Syst Saf 2021;216: 107924.
[28] Guilani PP, Ardakan MA, Dobani ER. Optimal component sequence in heterogeneous 1-out-of-N mixed RRAPs. Reliab Eng Syst Saf 2022;217:108095.
[29] Yeh W-C, Zhu W, Tan S-Y, Wang G-G, Yeh Y-H. Novel general active reliability redundancy allocation problems and algorithm. Reliab Eng Syst Saf 2022;218: 108167.
[30] Yeh W-C. BAT-based algorithm for finding all Pareto solutions of the series-parallel redundancy allocation problem with mixed components. Reliab Eng Syst Saf 2022; 228:108795.
[31] Chowdury MAM, Nath R, Shukla AK, Rauniyar A. Multi-task optimization in reliability redundancy allocation problem: a multifactorial evolutionary-based approach. Reliab Eng Syst Saf 2023:109807.
[32] Zhang J, Lv H, Hou J. A novel general model for RAP and RRAP optimization of k-out-of-n: G systems with mixed redundancy strategy. Reliab Eng Syst Saf 2023;229: 108843.
[33] Huang X, Coolen FPA, Coolen-Maturi T. A heuristic survival signature based approach for reliability-redundancy allocation. Reliab Eng Syst Saf 2019;185: 511–7.
[34] Sharifi M, Taghipour S. Redundancy allocation problem of a multi-state system with binary-state continuous performance level components. Expert Syst Appl 2022;200:117161.
[35] Sharifi M, Taghipour S. Optimizing a redundancy allocation problem with open-circuit and short-circuit failure modes at the component and subsystem levels. Eng Optim 2021;53(6):1064–80.
[36] Sharifi M, Taghipour S, Abhari A. Condition-based optimization of non-identical inspection intervals for a k-out-of-n load sharing system with hybrid mixed redundancy strategy. Knowl Based Syst 2022;240:108153.

[37] Sharifi M, Sayyad A, Taghipour S, Abhari A. Optimizing a joint reliability-redundancy allocation problem with common cause multi-state failures using immune algorithm. Proc Inst Mech Eng Part O J Risk Reliab 2023;237(1):152–65.
[38] Zhang Z, Yang L, Xu Y, Zhu R, Cao Y. A novel reliability redundancy allocation problem formulation for complex systems. Reliab Eng Syst Saf 2023;239:109471.
[39] Khalili-Damghani K, Abtahi A-R, Tavana M. A decision support system for solving multi-objective redundancy allocation problems. Qual Reliab Eng Int 2014;30(8):1249–62.
[40] Garg H, Rani M, Sharma SP, Vishwakarma Y. Bi-objective optimization of the reliability-redundancy allocation problem for series-parallel system. J Manuf Syst 2014;33(3):335–47.
[41] Salmasnia A, Ameri E, Niaki STA. A robust loss function approach for a multi-objective redundancy allocation problem. Appl Math Model 2016;40(1):635–45.
[42] Kayedpour F, Amiri M, Rafizadeh M, Nia AS. Multi-objective redundancy allocation problem for a system with repairable components considering instantaneous availability and strategy selection. Reliab Eng Syst Saf 2017;160:11–20.
[43] Zaretalab A, Sharifi M, Pourkarim Guilani P, Taghipour S, Niaki STA. A multi-objective model for optimizing the redundancy allocation, component supplier selection, and reliable activities for multi-state systems. Reliab Eng Syst Saf 2022;222:108394.
[44] Muhuri PK, Nath R. A novel evolutionary algorithmic solution approach for bilevel reliability-redundancy allocation problem. Reliab Eng Syst Saf 2019;191:106531.
[45] Zhao J, Si S, Cai Z. A multi-objective reliability optimization for reconfigurable systems considering components degradation. Reliab Eng Syst Saf 2019;183:104–15.
[46] Wang W, Lin M, Fu Y, Luo X, Chen H. Multi-objective optimization of reliability-redundancy allocation problem for multi-type production systems considering redundancy strategies. Reliab Eng Syst Saf 2020;193:106681.
[47] Azimi M, Mehdi A. Optimum number of cascade cells for multilevel inverter considering redundancy strategies based on cost and reliability optimization. IET Gener Transm Distrib 2023;17(19):4423–36.
[48] Azizi S, Mohammadi M. Strategy selection for multi-objective redundancy allocation problem in a k-out-of-n system considering the mean time to failure. OPSEARCH 2023;60(2):1021–44.
[49] Brockhoff D, Zitzler E. Are all objectives necessary? On dimensionality reduction in evolutionary multiobjective optimization. Parallel problem solving from nature-PPSN IX. Springer; 2006. p. 533–42. Berlin, Heidelberg.
[50] Tan KC, Khor EF, Lee TH, Sathikannan R. An evolutionary algorithm with advanced goal and priority specification for multi-objective optimization. J Artif Intell Res 2003;18:183–215.
[51] Matsumoto M, Abe J, Yoshimura M. A Multiobjective Optimization Strategy with Priority Ranking of the Design Objectives. ASME. J. Mech. Des. 1993;115(4):784–92.
[52] Gong J, Xie D, Jiang C, Zhang Y. Multiple objective compromised method for power management in virtual power plants. Energies 2011;4(4):700–16.
[53] Berrada I, Ferland JA, Michelon P. A multi-objective approach to nurse scheduling with both hard and soft constraints. Socioecon Plann Sci 1996;30(3):183–93.
[54] Aggelogiannaki E, Sarimveis H. A simulated annealing algorithm for prioritized multiobjective optimization—Implementation in an adaptive model predictive control configuration. IEEE Trans Syst Man Cybern Part B (Cybern) 2007;37(4):902–15.
[55] Li S, Hu C. Two-step interactive satisfactory method for fuzzy multiple objective optimization with preemptive priorities. IEEE Trans Fuzzy Syst 2007;15(3):417–25.
[56] Deb, K., and Saxena D.K.. "On finding pareto-optimal solutions through dimensionality reduction for certain large-dimensional multi-objective optimization problems." Kangal report 2005011 (2005): 1–19.
[57] Pozo C, Ruiz-Femenia R, Caballero J, Guillén-Gosálbez G, Jiménez L. On the use of principal component analysis for reducing the number of environmental objectives in multi-objective optimization: application to the design of chemical supply chains. Chem Eng Sci 2012;69(1):146–58.
[58] Hussain A, Kim H-M. Goal-programming-based multi-objective optimization in off-grid microgrids. Sustainability 2020;12(19):8119.
[59] Sharifi M, Taghipour S, Abhari A. Inspection interval optimization for a k-out-of-n load sharing system under a hybrid mixed redundancy strategy. Reliab Eng Syst Saf 2021;213:107681.
[60] Wu P, Gao L, Zou D, Li S. An improved particle swarm optimization algorithm for reliability problems. ISA Trans 2011;50(1):71–81.
[61] Kim H, Kim P. Reliability–redundancy allocation problem considering optimal redundancy strategy using parallel genetic algorithm. Reliab Eng Syst Saf 2017;159:153–60.
[62] Rauniyar A, Nath R, Muhuri PK. Multi-factorial evolutionary algorithm based novel solution approach for multi-objective pollution-routing problem. Comput Ind Eng 2019;130:757–71.
[63] Hsieh Y-C, You P-S. An effective immune based two-phase approach for the optimal reliability–redundancy allocation problem. Appl Math Comput 2011;218(4):1297–307.
[64] Wang L, Li L. A coevolutionary differential evolution with harmony search for reliability–redundancy optimization. Expert Syst Appl 2012;39(5):5271–8.
[65] Valian E, Tavakoli S, Mohanna S, Haghi A. Improved cuckoo search for reliability optimization problems. Comput Ind Eng 2013;64(1):459–68.
[66] Afonso LD, Mariani VC, Coelho LS. Modified imperialist competitive algorithm based on attraction and repulsion concepts for reliability-redundancy optimization. Expert Syst Appl 2013;40(9):3794–802.
[67] Kanagaraj G, Ponnambalam SG, Jawahar N. A hybrid cuckoo search and genetic algorithm for reliability–redundancy allocation problems. Comput Ind Eng 2013;66(4):1115–24.
[68] Ardakan MA, Hamadani AZ. Reliability–redundancy allocation problem with cold-standby redundancy strategy. Simul Model Pract Theory 2014;42:107–18.
[69] Liu Y, Qin G. A modified particle swarm optimization algorithm for reliability redundancy optimization problem. J Comput 2014;9(9):2124–31.
[70] He Q, Hu X, Ren H, Zhang H. A novel artificial fish swarm algorithm for solving large-scale reliability–redundancy application problem. ISA Trans 2015;59:105–13.
[71] Garg H. An efficient biogeography based optimization algorithm for solving reliability optimization problems. Swarm Evol Comput 2015;24:1–10.
[72] Huang C-L. A particle-based simplified swarm optimization algorithm for reliability redundancy allocation problems. Reliab Eng Syst Saf 2015;142:221–30.
[73] Liu Y. Improved bat algorithm for reliability-redundancy allocation problems. Int J Secur Appl 2016;10(2):1–12.
[74] Mellal MA, Zio E. A penalty guided stochastic fractal search approach for system reliability optimization. Reliab Eng Syst Saf 2016;152:213–27.
[75] Ouyang Z, Liu Yu, Ruan S-J, Jiang T. An improved particle swarm optimization algorithm for reliability-redundancy allocation problem with mixed redundancy strategy and heterogeneous components. Reliab Eng Syst Saf 2019;181:62–74.
[76] Juybari MN, Ardakan MA, Davari-Ardakani H. A penalty-guided fractal search algorithm for reliability–redundancy allocation problems with cold-standby strategy. Proc Inst Mech Eng, Part O J Risk Reliab 2019;233(5):775–90.
[77] Li S, Chi X, Yu B. An improved particle swarm optimization algorithm for the reliability–redundancy allocation problem with global reliability. Reliab Eng Syst Saf 2022;225:108604.