Soft Computing (2023) 27:14819–14833
https://doi.org/10.1007/s00500-023-08560-8

OPTIMIZATION

Reliability optimization and redundancy allocation for fire extinguisher drone using hybrid PSO–GWO

Ashok Singh Bhandari[1,2] · Akshay Kumar[2] · Mangey Ram[3]

Accepted: 18 May 2023 / Published online: 27 June 2023

Abstract

Reliability–redundancy allocation problem (RRAP) plays a vital role in reliability improvement and designing of systems which depend on the arrangement of components, reliability of the components, and redundancy allocation for the components. Higher reliability is the primary requisite for essential systems such as fire extinguisher drones (FEDs) which are very valuable for firefighters in tackling emergencies in non-reachable areas. In this work, a FED is considered with the aim of system designing for maximum reliability while considering the limited availability of resources such as volume, cost, and weight of the system. A total of five possible arrangements of the redundant components are investigated, and a mixed-integer nonlinear programming problem is solved for system reliability optimization. For optimization purposes, a recently developed metaheuristic hybrid particle swarm grey wolf optimizer (HPSGWO) is implemented. The HPSGWO is a powerful fusion of PSO's exploitation property and GWO's exploration property. Solving RRAP by using HPSGWO provides 99% reliability of the proposed FED under the limited availability of resources. To validate the superiority of the HPSGWO, a comparative study is explained.

Keywords Reliability–redundancy allocation problem · Fire extinguisher drone · Optimization · Mixed-integer nonlinear programming · Hybrid PSO–GWO

1 Introduction

Reliability is explained as the expectation that a product, structure, or resource will execute its intentional use acceptably for a prescribed time or will use in a specified domain without negligence. Product quality determines the success of the effect. One of the main features is the presentation of the product is fixed by reliability and redundancy. Reliability expands the current capability and expectations. To grow the overall reliability of any system, the reliability allocation problem (RAP) has turned into a question of extraordinary concern and interest recently. RAP is a kind of upgrade issue for restricting the system costs subject to the objective reliability limits (Yang et al. 1989). RAP means to choose two decision factors, the kind of parts and the number of parts, which is known as the excess level for each subsystem. In RAP, it is reliably acknowledged that there are some limited determinations of parts with predefined properties, for instance, reliability, weight, cost, and volume. In 1968, the specified procedure to handle RAP was portrayed, which was planned for the decision of the optimal course of action (Fyffe et al. 1968). After this, a few researchers proposed different procedures to address RAP in which the exact methods were done at first which were long handling techniques (Bellman and Dreyfus 1958; Tillman 1969; Luus 1975; Nam and Mitsuo Gen 1975), and later heuristic methodologies such as GA, PSO, hybrid GA–PSO, and hybrid PSO were considered (Nakagawa and Nakashima 1977; Yang et al. 1999; Sheikhalishahi et al. 2013; Liang et al. 2016). These heuristic methodologies were giving approximated results in almost no time when stood out from exact methods.

✉ Ashok Singh Bhandari
bhandariashoksingh@gmail.com

Akshay Kumar
akshaykr1001@gmail.com

Mangey Ram
drmrswami@yahoo.com

1 Department of Mathematics, School of Basic & Applied Sciences, Shri Guru Ram Rai University, Dehradun, India

2 Department of Mathematics, Graphic Era Hill University, Dehradun, Uttarakhand, India

3 Department of Mathematics, Computer Science & Engineering, Graphic Era Deemed to be University, Dehradun, Uttarakhand, India

On the other hand, the reliability–redundancy allocation problem (RRAP) attempts to find the best plan for a system, while the traits of parts are considered as decision factors. This issue makes the RRAP truly a testing issue for system designers and a more tangled issue for researchers. In this domain of reliability allocation, the greater part of the work and study is focused on the RRAP. The RRAP is a seriously difficult issue that can be detailed as a nonlinear mixed-integer programming problem with a specific set of nonlinear constraints. The essential goal of RRAP is to observe the number of repetitive parts and the reliability levels of every part to amplify the system's reliability. It has now been demonstrated that some RRAP can be NP-hard and for addressing such RRAP researchers have created numerous techniques and calculations (Chern 1992; Ardakan and Hamadani 2014; Hsieh et al. 1998; Wu et al. 2011; Wang and Li 2012; Afonso et al. 2013; Abouei Ardakan and Zeinal Hamadani 2014; Kim and Kim 2017; Kanagaraj et al. 2013). In this space, a penalty-guided artificial immune algorithm was introduced to tackle the reliability allocation problem. This calculation was competent to find the doable area for optimal arrangement (Chen 2006). A penalty-guided artificial bee colony calculation (ABC) was likewise executed to address RRAP where the goal was the reliability of parts, and the requirement was the expense of the system. Creators all the while investigated the number of repetitive parts and their respective reliability to amplify the system's reliability (Yeh and Hsieh 2011). Other methods such as soft computing approach (Gen and Yun 2006), simulated annealing approach (Kim et al. 2006), genetic algorithm (GA) (Yokota et al. 1996), immune-based two-phase approach (Hsieh and You 2011), cuckoo search (CS) (Valian and Valian 2013), and hybrid CS–GA algorithm (Kanagaraj et al. 2013) are also implemented to solve RRAP for the benchmark systems and improve reliability. Recently proposed algorithm hybrid PSO–GWO (Bhandari et al. 2023) has shown remarkable outcomes among the literature results for RRAP. The proposed hybrid PSO–GWO has obtained a reliability level of 93% for the series system and 99% for bridge, series–parallel, and overspeed protection system for gas turbine. Many creators have likewise dealt with the multi-objective reliability–redundancy problem (MORRAP) where reliability and cost had been taken as two unique goals for a system and the two targets were enhanced. In MORRAP, the execution of PSO gave Pareto-optimal solution rather than a single optimal (Zhang and Chen 2016; Garg and Sharma 2013; Khalili-Damghani et al. 2013).

By and large, there are two ordinary and seen sorts of redundancy called active and cold backup excess. In the last part of the 1990s, much work has been accounted for active redundancy allocation. For a series system, the issue of equal lifetime distributed components has been considered in Shaked and Shanthikumar (1992) and Singh and Singh (1997). Several authors have dealt with a couple of active redundancies designation to a k-out-of-n: G system to work on the system in the feeling of the likelihood request (Boland et al. 1992; Mi 1999) and multiple active redundancies in k-out-of-n: G system was concentrated (Garg and Sharma 2013; Shaked and Shanthikumar 1992; da Costa Bueno and do Carmo 2007). The cold-standby redundancy methodology was executed with a modified genetic algorithm (GA). This technique was applied to take care of nonlinear mixed-integer issues, and the outcomes were superior to past arrangements (Ardakan and Hamadani 2014; Hsieh et al. 1998; Wu et al. 2011; Wang and Li 2012; Afonso et al. 2013; Abouei Ardakan and Zeinal Hamadani 2014; Zou et al. 2011). Regarding the optimal excess procedure, progressed RRAP was presented for a cold-standby redundancy. This high-level RRAP with a nonlinear mixed-integer problem was addressed by parallel GA (Kim and Kim 2017). Afterwards, a hybrid technique was carried out other than active and standby redundancy to settle RRAP. Without a doubt, this procedure had shown a surprising improvement in optimal solutions (Abouei Ardakan et al. 2016). In the space of metaheuristic procedures, RRAP was likewise tackled by cuckoo search (CS) which was hybridized with GA. This hybridization yielded incredibly productive and powerful optimal solutions (Kanagaraj et al. 2013), but recently proposed algorithm hybrid PSO–GWO (Bhandari et al. 2022) for cold-standby strategy has shown better results in comparison with previous algorithms for RRAP.

2 Related work and motivation

Though, titanic work has been done in RAP and RRAP in which a few critical ways of thinking and techniques are applied to find the specific or the optimal answer for any system to be profoundly dependable. In a similar domain, Mellal and Williams implemented GA, PSO, and CS to solve a large-scale system reliability–redundancy allocation problem involving 20 subsystems (Arezki Mellal and Williams 2018). The reliability of a supervisory control and data acquisition system (SCADA) of Tehran was optimized by using RAP with limited availability of budget and other resources. In the presented work, cost minimization and reliability maximization were two objectives and therefore a bi-objective RAP was considered and multi-objective PSO was implemented to attain solutions (Dolatshahi-Zand and Khalili-Damghani 2015). Yeh and Lin considered smart sensor systems for RAP implementation, and the parallel simplified swarm algorithm (PSSO) was proposed for optimization purposes (Yeh and Lin 2018). Recently, the RRAP was investigated in a multistate flow network (MFN) in terms of cost minimization or reliability maximization under resource restrictions. The authors offered a basic cut-based approximation approach to convert NP-hard mixed-integer nonlinear programming problem into an integer programming problem (Zhang et al. 2022). Other than system engineering, the optimization process is also implemented in the medical and food sectors. In this domain, modified convolutional (CNN) and convolutional autoencoder (Conv-AE) neural networks (NNs) were implemented for classifying data from scalp EEG recordings into Alzheimer's disease (AD), mild cognitive impairment (MCI), and healthy control (HC) (Fouladi et al. 2022). Similarly, image processing techniques, texturing, neural networks, and adaptive network-based fuzzy inference system (ANFIS) classifiers were also proposed to diagnose Alternaria disease and leaf miner pest (Nazari et al. 2022). Other than reliability optimization, metaheuristic algorithms are also implemented in other fields such as adaptive polyploid memetic algorithm (APMA) implemented for the problem of scheduling CDT trucks that can assist with proper CDT operations planning (Dulebenets 2021). A universal island-based metaheuristic algorithm (UIMA) was proposed to handle the spatially constrained berth scheduling problem. This population-based metaheuristic algorithm was implemented to solve the berth scheduling problem and minimize the total cost of serving the arriving vessels at the marine container terminals (Kavoosi et al. 2020). Non-dominated sorting genetic algorithm II (NSGA-II) and multi-objective particle swarm optimization (MOPSO) are used to find high-quality solutions for ambulance routes in a short period and minimize the latest service completion time as well as the number of patients whose condition worsens due to receiving delayed medical services (Rabbani et al. 2022).

Most of the work in the literature in the domain of RRAP is dedicated to improving the reliability of benchmark systems with different algorithms and different strategies. As discussed above, some authors have contributed to the reliability analysis and optimization of some complex and useful systems; thus, in this research work RRAP is applied meanwhile for a very useful complex system FED. The RRAP tended in this paper is of incredible useful importance. System designers work to make decisions concerning the level of redundancy in all subsystems to achieve maximum reliability while setting the cost, volume, and weight of the system as low as possible. System designers can defeat this issue either by using redundant parts to make the system desired reliable or by further developing the reliability of the parts which will achieve reliability improvement of parts. Notwithstanding, by then, the essential issue arises that directly affects the cost of the whole system. Therefore, our point in this work is to pick which design or arrangement is more compelling for the designers in keeping the cost low. Additionally, the HPSGWO algorithm is developed for addressing the nonlinear mixed-integer programming problem. The main highlights of the proposed work are as follows:

- RRAP is applied on FED to maximize the system reliability with some imperatives such as parts and the system's cost, weight, and volume.
- The notable HPSGWO algorithm is developed for addressing the nonlinear mixed-integer programming problem.
- The study of standard deviation between GWO and HPSGWO shows a high convergence of HPSGWO than GWO.
- A total of five designs of FED with different levels of redundancy are solved for reliability optimization.
- The comparative study of maximum reliability among all designs makes it easy for system designers to choose a highly reliable system.
- Also, the comparative study among the slack variables or unused resources opens another dimension for system designers to think of. Designers can make an ideally designed system by considering the trade-off between system reliability and slack variables.

We have isolated this work into nine areas. The first section depicts the introduction of RAP and RRAP, and the second section explains the motivation for the current work. The third section explains the components and workings of the FED. The fourth section portrays the assumptions and notations which are implemented in this work. The fifth section explains the mathematical model for FED in which the nonlinear mixed-integer programming problem is stated. The sixth section is an explanation of the working procedure of the GWO algorithm, while the seventh section describes the working and efficiency of HPSGWO. The eighth section presents and discusses the outcomes obtained from the implementation of the HPSGWO algorithm to optimize the reliability of FED, and the last section concludes and explains the future scopes of this work in system designing.

3 Fire extinguisher drone

The FEDs are very valuable for firefighters in tackling emergencies in non-reachable areas. Fire sometimes makes gigantic misfortune to our untamed life, normal assets, woods, human existence, etc. According to the Times of India report, in 2017 out of 27,027 demises, each fifth Fire-associated demise on the planet occurred in India. Approximately 90 lakh Fire occurrences and 1.2 lakh demises were noted around the world that year. Thirty-five Indians pass on in these fire mishaps every day, according to the National Crime Records Bureau (NCRB). Quick admittance to fire and moment quenching are vital to counter fire dangers, and the drone procedure is probably the most ideal way of dousing the fire as it works where people cannot reach because of the most exceedingly terrible state of fire. Indeed, even here and there it quenches the fire before it transforms into a devil. There are some problems that firefighters face in various situations such as some forest wildfires that begin in central forest areas that are difficult to get control by the time firefighters reach there with a water supply and fire brigade the fire already covers other areas of forest. Firefighting transport supplies water for showering on multi-story building fires, leading to major misplays. These buildings are residents for thousands of people. Firefighters risk their lives to secure others' life in fire emergency zones. Risks include heat exhaustion, burns, and physical and mental stress. The drone helps firefighters calm fire beat out without being in danger. Secondly, instantly it can access forest areas which would consume hours for fire equipment and humans to reach the emergency zones and quickly reach multi-story building windows along with fire extinguishers.

3.1 Components of FEDs

The main components of FED are a fire extinguisher ball, camera, LED lights, motors, controller, propellers, sensors, and transmitter. Fireball is constructed on revolutionary mechanics which supply much more up-to-date solutions compared with transportable fire extinguishers. The constraints and issues related to ordinary techniques of extinction (conservation, training, etc.) are at the beginning of its expansion. It is comfortable to utilize and supply shelter as it is self-concern in the existence of a blaze in the absence of human interference.

The passive infrared (PIR) motion detectors are outlined for safety and enhanced to accurately discover human beings, big pets, and extra huge friendly working things. Also, we could utilize a thermal visualizing camera. The supply of light is needed in unlighted places, and it is also helpful to get dazzling and sharp pictures from the camera.

The motors used in drones are of two types: brushed and brushless motors. These motors differ in the method they perform tasks. The brushless method is extra significant for its heaviness than brushed motors, and they rearmost way prolonged. The drone regulator permits the drone commander to manage the drone utilizing radio waves. Electronic speed controllers are gadgets that permit drone flight regulators to manage and alter the speed of the drone. All unmanned aerial vehicles (UAV) are driven by a set of revolving blades, raising them onward to force them to fly. Drone rotors are the revolving wings that behave as the quadcopter's pennon or wings which generate current to raise it in the direction of air.

Tilt detectors or sensors merged with gyros and accelerometers, supply instructions to flight management structures conducive to continuing the level flight.

Drone radio transmitter is an electronic gadget that makes use of radio signals to circulate order wirelessly through a set radio recurrence above the radio receiver, which is attached to an aircraft or aero drone being remotely managed.

3.2 Working of FED

Initially, the signals of fire situations are transmitted through transmitters which are received by the drone receiver. Then, these signals go to the accelerometer and gyroscope sensors via the flight controller. The refined sign will be passed on to the ESC, which allows the particular add-up to the motor depending on the sign it gets. The propellers are consequently combined with the motors with the goal that they can turn and create push. A servo engine controlled through a transmitter is applied to open the shell in which the discharge quencher ball is held inside. The stream cost of the pump can likewise be controlled through the transmitter.

4 Assumptions and notations

Before delving into the reliability–redundancy allocation problem, we specify the following: assumptions and notation, which will be used throughout the work. The notations are shown in nomenclature section, and the assumptions are as follows (Kundu and Garg 2022):

- There is an infinite supply of components.
- Each component in a subsystem has the same reliability, cost, weight, and volume.
- Failing components do not do any harm to the system and are not getting repaired.
- All redundancies are active: the hazard function is the same whether it is used or not used.
- Individual component failures are independent.

The list of notations used in the HPSGWO algorithm for optimization is given in Table 1 (Kundu and Garg 2022).

5 Mathematical formulation of FED

Figure 1 represents the block diagram of FED where four subsystems are arranged in series. The second and fourth subsystem has two and four components arranged in parallel, respectively. Here in this paper, five cases for optimization are considered where each case has a different design or redundancy arrangement. All the designs satisfy the constraints utilizing cost, volume, and weight. The mathematical modelling for FED reliability optimization is explained as follows (Kanagaraj et al. 2013):

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

Subject to

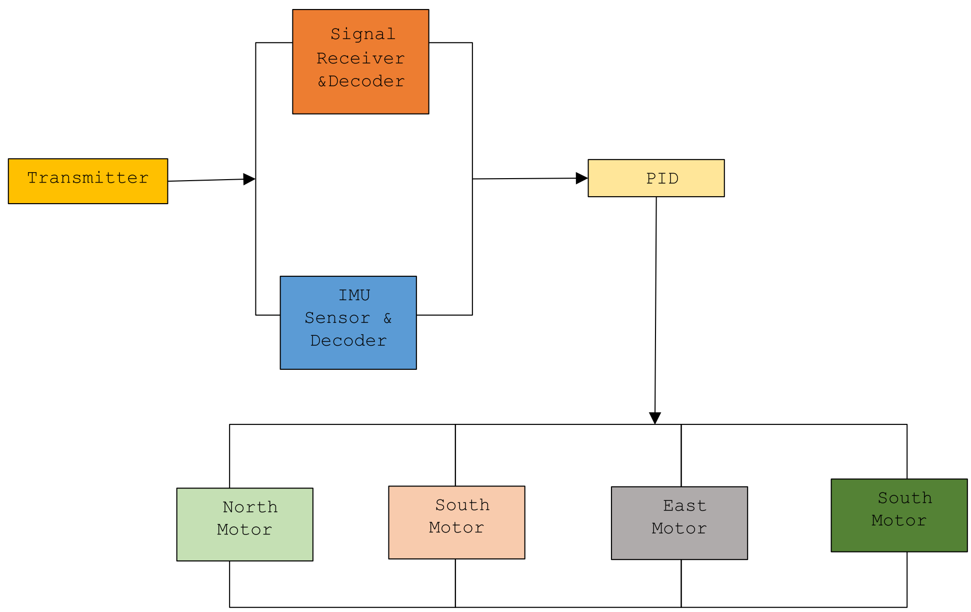
$$g_1(r,n) = \sum_{i=1}^{m} w_i \cdot v_i^2 \cdot n_i(j)^2 \le V \tag{2}$$

Table 1 Notations

m	The number of subsystems in the system
n_i	The number of components in ith subsystem
n	$\equiv (\boldsymbol{n}_1, \boldsymbol{n}_2, \ldots, \boldsymbol{n}_m)$ the vector of the redundancy allocation for the system
r_i	The reliability of each component in ith subsystem
r	$\equiv (\boldsymbol{r}_1, \boldsymbol{r}_2, \ldots, \boldsymbol{r}_m)$ the vector of the component reliabilities for the system
R	System reliability
g_i	**ith** constraint
v_i	The volume of each component in ith subsystem
w_i	The weight of each component in ith subsystem
c_i	The cost of each component in ith subsystem
V	The upper limit on the volume of the system
C	The upper limit on the cost of the system
W	The upper limit on the weight of the system
$f(r, n)$	System reliability

Bold values mean the improved results

Fig. 1 Block diagram of FED



$$g_2(r, n) = \sum_{i=1}^{m} \alpha_i \cdot \left(-\frac{1000}{\ln r_i}\right)^{\beta_i} \cdot [n_i + e^{0.25 n_i(j)^2}] \leq C \quad (3)$$

$$g_3(r, n) = \sum_{i=1}^{m} w_i \cdot n_i \cdot e^{0.25 n_i(j)} \leq W \quad (4)$$

where, $n_i \in \mathbb{Z}^+$, $0 \leq r_i \leq 1, r_i \in \mathbb{R}, 1 \leq j \leq 5$

Equations (2), (3), and (4) represent the constraints that are volume, cost, and weight of the system, respectively. Here, constraint (2) is a product of the weight, volume, and redundancy level of the system which is restricted by the maximum required volume for the system. Constraint (3) is a cost constraint for the system that depends on the reliability of the component, and constraint (4) is a combination of weight and redundancy level of the system. Table 2 depicts the list of the values of the input parameters that are used in the constraints. α_i and β_i represent the physical features of ith subsystem. The values of all the input parameters are considered the same as (Dhillon et al. 2022). The similar values of $\boldsymbol{\alpha_i}$, β_i, $w_i.v_i^2$, and w_i are considered in Kanagaraj et al. (2013), Kim et al. (2006), Hsieh and You (2011), Kanagaraj et al. (2013), Bhandari et al. (2023), Kim and Kim (2017), and Li et al. (2022).

6 Overview of GWO

The GWO algorithm is inspired by grey wolves (Canis lupus). The GWO algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature.

Table 2 Values of the constraints used in the optimization problem

n	$10^5.\alpha_i$	β_i	$w_i.v_i^2$	w_i	V	C	W
1	2.330	1.5	1	7	400	300	350
2	1.450	1.5	2	8			
3	0.541	1.5	3	8			
4	8.050	1.5	4	6			
5	1.950	1.5	2	9			

The social direct and moderate mindset among the wolves are ruling, and this lead prompts a useful hunting part (Mirjalili et al. 2014). This social information on the wolves, the power of the pioneer wolf that is alpha (α), and the other three in number wolves in the pack that is beta (β), delta (δ), and omega (ω) close by the adaptable part of looking, moving closer, in conclusion, hunting the prey are the three essential prodding factors behind the reasonable working of the GWO computation. This is copied in finding the overall ideal arrangement from complex issues of different fields of designing and innovation. The hunting system of wolves incorporates pursuing, enclosing, and hunting which is numerically shown in the following.

6.1 Social hierarchy

In the inclusion of mathematical representation, when plotting GWO, the social hierarchy of wolves examines the best solution as the alpha (α). Thus, the second and third finest solutions are termed beta (β) and delta (δ), respectively. The remaining possible solutions are presumed to be omega (ω). The hunting is led by α, β, and δ in the GWO process. These three wolves are followed by ω wolves.

6.2 Encircling prey

In addition to mathematically model circumscribing habits, the following calculations are suggested:

$$\vec{D} = |\vec{C} \cdot \vec{X}\mathrm{p(t)} - \vec{X}\mathrm{(t)}| \tag{5}$$

$$\vec{X}(\mathrm{t+1}) = \vec{X}\mathrm{p(t)} - \vec{A} \cdot \vec{D} \tag{6}$$

where t denotes the current iteration, $\vec{A}$ and $\vec{C}$ are the coefficient vectors, $\vec{X}$ p is the position vector of the predator, and $\vec{X}$ indicates the position vector of a grey wolf.

The vectors $\vec{A}$ and $\vec{C}$ are considered in this way:

$$\vec{A} = 2\vec{a} \cdot \vec{r}1 - \vec{a} \tag{7}$$

$$\vec{C} = 2 \cdot \vec{r}2 \tag{8}$$

where elements of $\vec{\boldsymbol{a}}$ are directly reduced from 2 to 0 above the course of repetitions and r_1, r_2 are the random vectors in [0, 1].

6.3 Hunting

Grey wolves first recognize the position of prey and then encircle them, and this is one of their abilities. The chase is generally led by the alpha. The beta and delta may also engage in chasing traditionally. But, in a theoretical probe location, we have no indeed suggestion regarding the situation of the predator. In addition to mathematically imitating the chasing habit of grey wolves, we assume that the alpha, beta, and delta have a finer understanding regarding the possible position of prey.

The following formulas are preferred in this view:

$$\vec{D}\alpha = \left|\vec{C}_1 \cdot \vec{X}\alpha - \vec{X}\right|, \vec{D}_\beta = \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right|, \vec{D}_\delta = \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}\right| \tag{9}$$

$$\vec{X}_1 = \vec{X}\alpha - \vec{A}_1 \cdot \left(\vec{D}\alpha\right), \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \left(\vec{D}_\beta\right), \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot (\vec{D}_\delta) \tag{10}$$

$$\vec{X}_{t+1} = (\vec{X}_1 + \vec{X}_2 + \vec{X}_3)/3 \tag{11}$$

It is noticeable that the last location would be at an arbitrary point within a circle which is explained by the locations of alpha, beta, and delta in the hunt area.

6.4 Attacking predators

When the predator ends moving, the grey wolves complete the hunt by striking the predator. In conducive to mathematical imitation proceed towards the predator, we degrade the value of $\vec{\boldsymbol{a}}$. Record that the movement interval of $\vec{A}$ is further diminished by $\vec{a}$. In addition, $\vec{A}$ is an arbitrary value in the interval [− 2a, 2a] where a is diminished from 2 to 0 throughout repetitions. Whenever arbitrary values of $\vec{A}$ lie in [1,1], the upcoming location of an explorer agent could be in any location between its present location and the location of the predator.

6.5 Searching for predators

Grey wolves mainly hunt confirming the location of the alpha, beta, and delta. They separate from one another to hunt for predators and assemble to pounce on predators. According to mathematical model divergence, we employ $\overrightarrow{A}$ with general values above 1 or below -1 to bind a search agent to deviate from the predator. This highlights the survey and permits the GWO technique to hunt worldwide.

To look at how GWO is capable of tackling optimization problems, several points can be prominent:

The suggested organized grading helps GWO to rescue the finest solutions acquired until now over the journey of repetition. The preferred surrounding process describes the circle-formed locality throughout the solutions which could be prolonged to excessive measurements as a hyper-sphere.

The arbitrary variables A and C help applicant solutions to have hyper-spheres with discrete arbitrary radii. The suggested trapping technique permits applicant solutions to find the expected place of the predator. Investigation and misuse are promised by the flexible values of a and A. The flexible values of variables a and A allow GWO to evenly change between survey and misuse. With slackening A, partially of the repetition are constant to investigation and the other parts are devoted to misuse. In GWO, there are only two important variables that have to be balanced (A and C).

7 Proposed Algorithm: HPSGWO

The proposed HPSGWO calculation has been done without changing the general movement of the PSO and GWO calculations. The PSO calculation is adequately proficient to track down upgraded outcomes in practically all intricate issues (Kennedy 1995). In any case, there is a requirement for the diminished opportunities for the PSO to stall out into the nearby ideal arrangements. In HPSGWO, the GWO calculation helps the PSO calculation to reduce the shot of falling into an area ideal (Şenel et al. 2019). Additionally, the GWO calculation's investigation quality forestalls the odds of particles creating some distance from the worldwide ideal by guiding the particles to advanced situations rather than new arbitrary positions. HPSGWO is constituted by the combination of the upgraded GWO and improved PSO. Firstly, set the frameworks and deallocate the positions and velocities of the particles anyhow. Compute the strength value of each representative, classify the population in decreasing order as stated by the fitness values, and decide g_{best}, p_{best}, X_α, X_β, and X_δ. For the benefit of expression, g_{best} and X_α are two discrete forms of the worldwide finest solution. Choose the modernized method to renovate the current particle following the poor-for-change policy. Accurate the velocities and places of all the particles and compute the fitness values. Organize the population in a decreasing order following the fitness values and renovate g_{best}, p_{best}, X_α, X_β, and X_δ. Decide whether the conclusion condition is well pleased or not. If the condition is not satisfied, go back to Step 3, or else, output the best answer.

Pseudo Code for HPSGWO

```
1.  Maxit: The maximum number of iterations
2.  N: Population size
3.  p_r: Small possibility rate of being the local best
4.  start procedure: HPSGWO
5.  Initialization of particles
6.  for i = 1: Maxit
7.      for j = 1: N
8.          Run PSO
9.              Update the particle's position and velocity by using PSO
10.             if rand (0,1) < p_r                (to avoid local best particle)
11.                 Set coefficients A and C for the encircling vectors in GWO
12.                     for i = 1: 100
13.                         for j = 1: 100
14.                             Run GWO
15.                             Update the best three wolves' (α, β, and δ) position
16.                                 Update A and C
17.                         end
18.                     end
19.                 positon of current particle = mean of α, β, δ
20.             end
21.         end
22.     end
23. end procedure
```

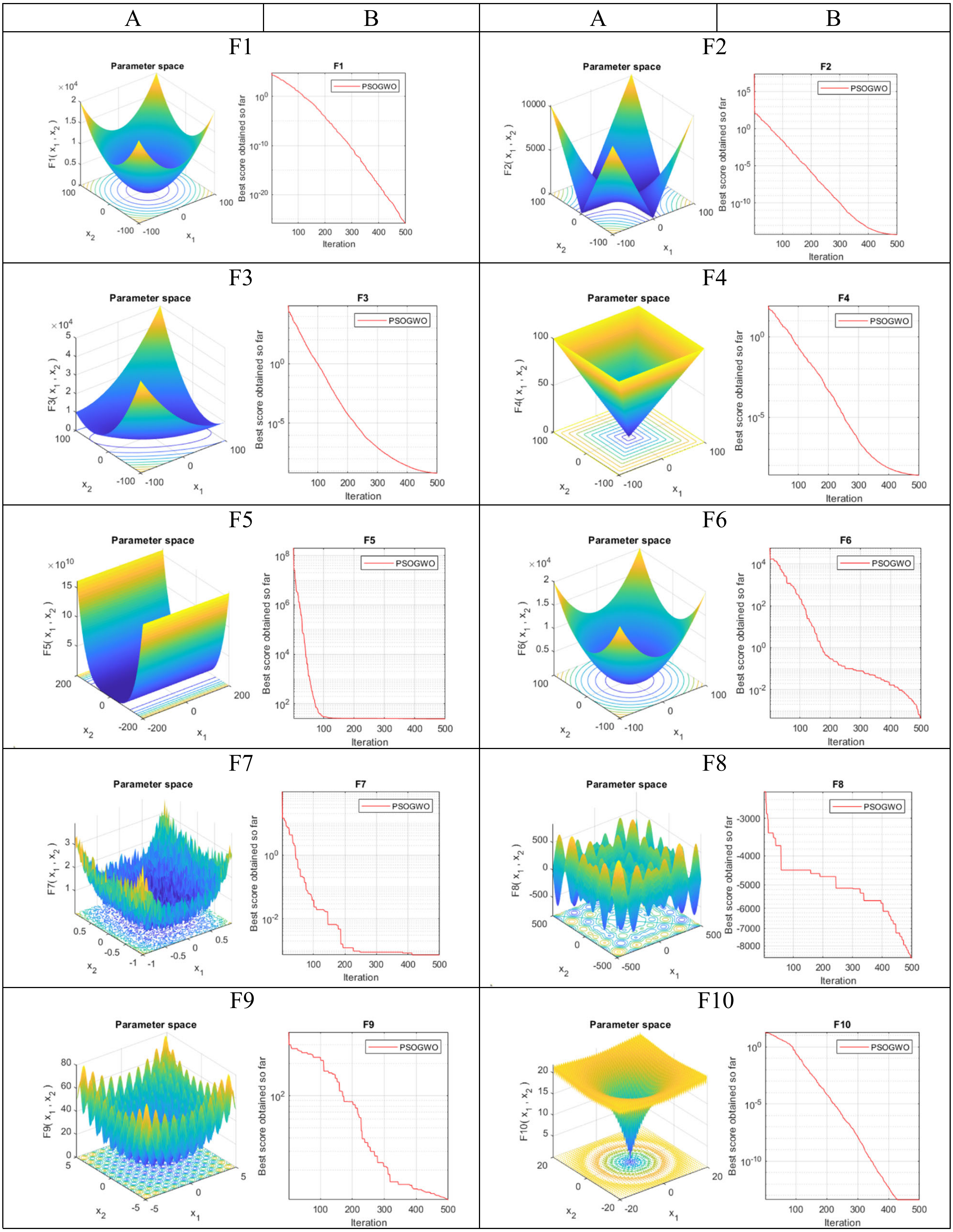


Fig. 2 Benchmark functions from F1–F23, **A** 2D function plot and **B** convergence characteristics with the proposed algorithm

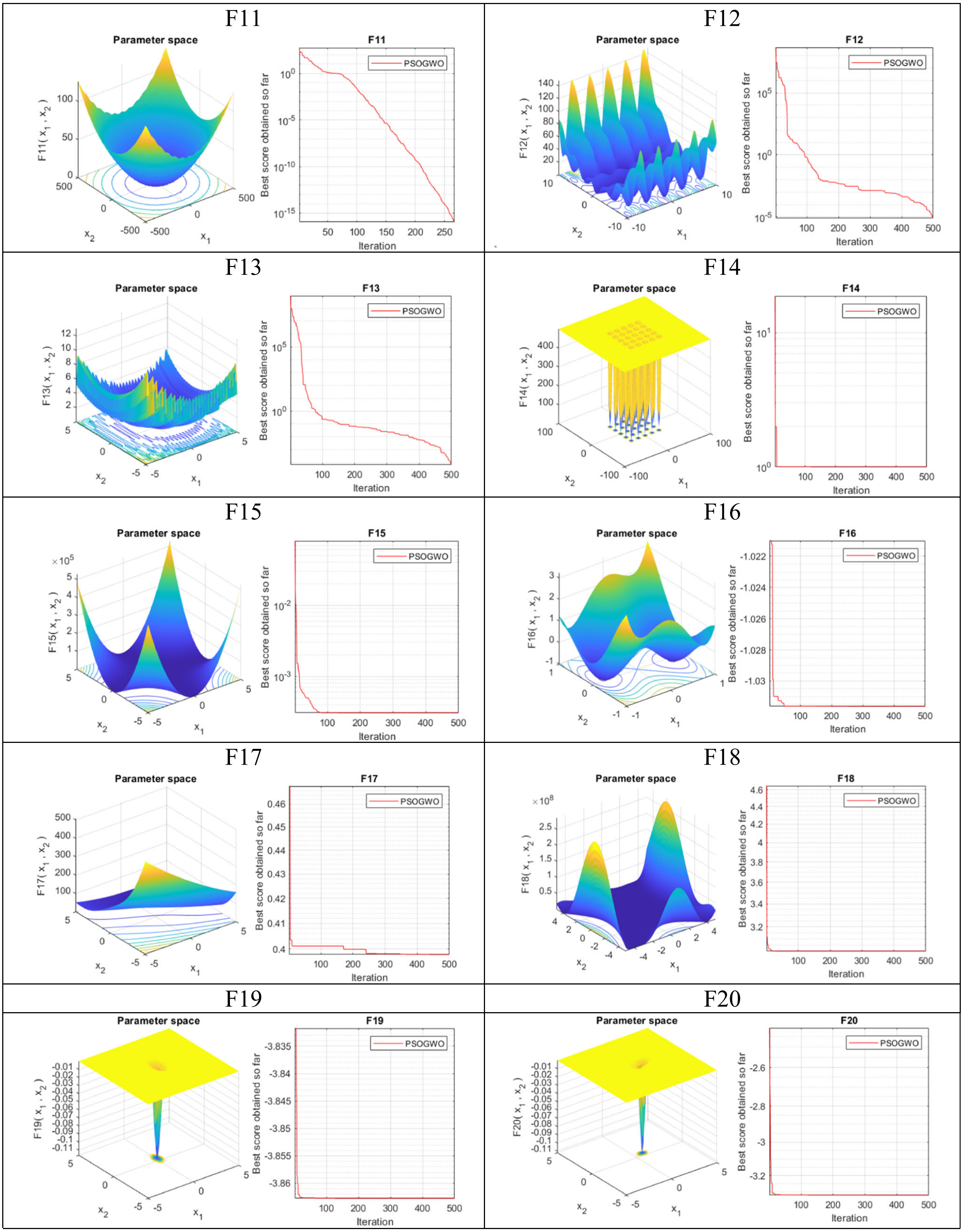


Fig. 2 continued

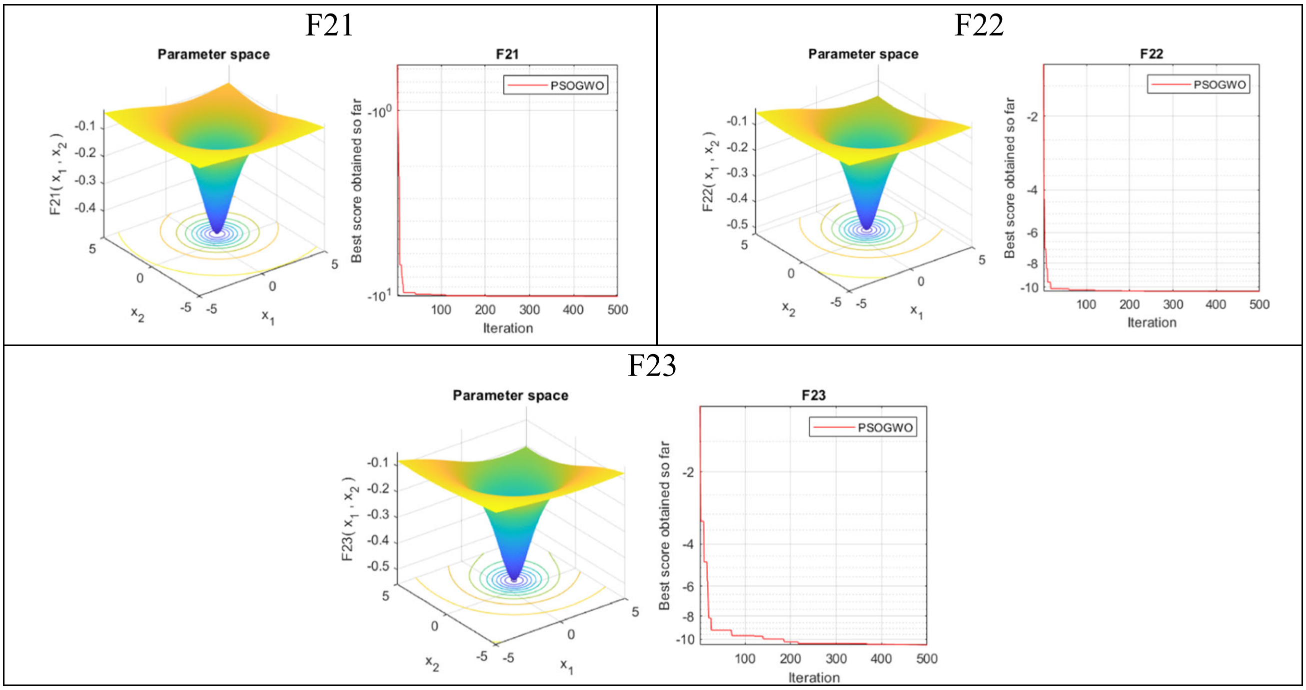


Fig. 2 continued

Figure 2 depicts the performance of the suggested approach for the 23 benchmark functions F1–F23. Figure 2A depicts the two-dimensional (2D) representation of the three-dimensional (3D) parameter space, and Fig. 2B depicts the convergence characteristics of the proposed technique with respect to the number of iterations. The convergence characteristics are plotted by taking into account the mean values of optimal values for the ten different runs in each iteration, and the proposed algorithm has the mixed behaviour of integrated algorithms, resulting in efficient system performance. Table 3 shows the results of the statistical analysis using the proposed technique on the benchmark functions. To analyse the efficiency of the proposed hybrid PSO–GWO, the proposed method is compared to the most recent hybrid algorithm called MGWO–SCA–CSA using algorithm parameters of population size 100 and total number of iterations 500. Table 2 shows the mean, standard deviation, best, and worst values obtained from ten different runs (Dey et al. 2021).

The outcomes are presented in Table 3, which explains the efficiency of the proposed algorithm to achieve global optimal for an optimization problem. The high standard deviation for iterations is due to the high exploration property of GWO, and the best outcomes are achieved by the high exploitation property of PSO (Şenel et al. 2019).

8 Outcomes and discussion

In Table 3, the results were obtained from a developed algorithm for RRAP from MATLAB software. The different redundancy levels best, worst, mean, and standard deviation of the GWO and HPSGWO are mentioned in Table 4. n_i is the redundancy level for subsystems, *f(r,n) best* is the maximum value of system reliability, and *f(r,n) worst* is the minimum value for all 20 runs.

In Table 5, the maximum achieved reliability for the FED and optimal reliability for the components in each redundancy level of FED are presented. Also, the comparison of the system's as well as components' reliability between the GWO and HPSGWO is mentioned. It is evident from Table 5 that in all the considered redundancy levels for the system the HPSGWO has achieved better reliability as compared to GWO. In terms of highly reliable allocation of redundancy, the system with redundancy level [5 2 2 6 2] can be an ideal choice for designers. Other factors like resources like consumption of cost, weight, and volume are calculated for each redundancy level and optimal reliability in Table 6.

Table 6 shows the remaining amount of available resources after attaining optimal reliability which can be an important prospect for system designers. Designers can opt for such a system design that meets their particular requirements perfectly. The designers can check the usage of available resources from Table 6 and construct some

Table 3 Comparison of outcomes for CEC benchmark functions

CEC Function	MGWO–SCA–CSA				Hybrid PSO–GWO			
	Mean	Std. deviation	Best	Worst	Mean	Std. deviation	Best	Worst
F1	2.76E − 17	3.30E − 17	1.42E − 18	1.56E − 16	1.010E + 03	4.47798E + 03	**1.32E − 26**	6.58E + 04
F2	1.45E − 10	1.04E − 10	3.98E − 11	5.08E − 10	5.2601E + 04	1.17612E + 06	**5.31E − 15**	2.63E + 06
F3	2.04E + 00	2.42E + 00	1.21E − 01	7.80E + 00	6.8989E + 02	4.4076E + 03	**6.50E − 10**	7.69E + 04
F4	2.02E − 04	1.22E − 04	4.48E − 05	4.85E − 04	2.6971	9.511646	**2.47E − 09**	85.1761
F5	25.4669068	0.44565548	24.4619501	26.9798566	7.6532E + 05	9.46571E + 06	**24.33519**	2.04E + 08
F6	0.05496559	0.11011342	8.88E − 03	0.50624229	1.2335E + 03	4.27924E + 03	**4.31E − 04**	5.69E + 04
F7	0.00334014	0.00157199	1.13E − 03	0.00777797	0.8190	4.983020	**0.731E − 03**	99.32832
F8	− 7313.101	558.956181	− 8410.11055	− 6038.45481	− 5.190E + 03	1.25398E + 03	**− 8776.395**	− 2.44E + 03
F9	8.70E + 00	1.11E + 01	**2.36E − 08**	6.19E + 01	9.2909E + 01	9.67607E + 01	10.5693	3.95E + 02
F10	1.12E − 09	6.72E − 10	1.69E − 10	2.90E − 09	1.3299	3.62452	**4.35E − 14**	2.00E + 01
F11	4.68E − 03	1.24E − 02	**0**	6.18E − 02	4.5905	3.20514E + 01	**0**	5.78E + 02
F12	4.33E − 03	4.55E − 03	3.48E − 04	1.59E − 02	1.2614E + 06	2.09724E + 07	**7.81E − 06**	4.66E + 07
F13	0.07002191	0.06298713	4.20E − 03	0.23118712	3.1545E + 06	4.29964E +	**0.07E − 03**	9.41E + 07
F14	4.6525015	4.30646153	**0.99800**	12.6705058	1.0440	0.799806	**0.99800**	1.87E + 01
F15	0.00714846	0.00950536	0.00030941	0.02036335	5.9721E − 04	3.712969E − 03	**0.000307**	8.03E − 02
F16	− 1.03162842	3.28E − 08	**− 1.03162845**	− 1.03162829	− 1.030	1.383683E − 02	**− 1.031628**	− 7.6E − 01
F17	0.39788908	2.18E − 06	**0.39788737**	0.39789664	0.39992	6.29541E − 03	0.397892	4.68E − 01
F18	3.0000027	4.10E − 06	**3**	3.0000178	3.0045	7.419196E − 02	**3**	4.64832
F19	− 3.8627699	1.97E − 05	− 3.86278187	− 3.86267523	− 3.86235	3.31361E − 03	**− 3.862782**	− 3.83178
F20	− 3.2878428	0.05854798	− 3.32198424	− 3.1383395	− 3.31555	5.68333E − 02	**− 3.321995**	− 2.4104
F21	− 7.23145613	3.47126096	− 10.1516347	− 2.63032641	− 9.945077	0.92729	**− 10.15297**	− 0.564985
F22	− 9.45389728	2.46677597	− 10.4026621	− 2.75083171	− 10.25479	0.653162	**− 10.40291**	− 1.22498
F23	− 8.98285371	3.14932953	− 10.5343955	− 2.42146394	− 9.89407	1.28168	**− 10.53573**	− 1.06411

Bold values mean the improved results

Table 4 Convergence results of the objective function (20 runs) for the FED system using GWO and HPSGWO

Algorithm	n_i	$f(r,n)$ best	$f(r,n)$ worst	Mean	Standard deviation
GWO	[4 3 3 4 4]	0.9997952654	0.9993643922	0.9997030267	1.3721907e − 04
	[4 4 5 2 3]	0.9986015023	0.9964571882	0.9979454068	0.0006162371
	[4 4 4 4 4]	0.9998620296	0.9995771064	0.9997355099	9.0143132e − 05
	[5 5 4 3 3]	0.9998620086	0.9993076885	0.9996985681	0.0001313735
	[5 2 2 6 2]	0.9998589722	0.9993308848	0.9997193323	0.0001295686
HPSGWO	[4 3 3 4 4]	0.9999012585	0.9998860791	0.9998985325	5.0247741e − 06
	[4 4 5 2 3]	0.9991398821	0.9989167074	0.9991152434	4.9910537e − 05
	[4 4 4 4 4]	0.9999180064	0.9998985177	0.9999161568	4.3135261e − 06
	[5 5 4 3 3]	0.9999140900	0.9998925693	0.9999117458	4.7870377e − 06
	[5 2 2 6 2]	0.9999387780	0.9999204537	0.9999351080	5.6176289e − 06

Table 5 System reliability and components' reliability for FED

Redundancy level	Parameters	GWO	HPSGWO
[4 3 3 4 4]	R_{system}	0.999795265420947	**0.999899747608588**
	r_1	0.898363507342117	0.90972267301366
	r_2	0.810356036764371	0.761213640113273
	r_3	0.881103491628621	0.907357745283414
	r_4	0.903625594230794	0.931906835870775
	r_5	0.608344603658741	0.567336687730478
[4 4 5 2 3]	R_{system}	0.998601502346172	**0.999139882128989**
	r_1	0.860536792391562	0.876639558984553
	r_2	0.790695557445282	0.604999315358789
	r_3	0.627737508801209	0.766116002068882
	r_4	0.968268948142934	0.975413150992711
	r_5	0.776229994461219	0.627458076911624
[4 4 4 4 4]	R_{system}	0.999862029651366	**0.999918006368587**
	r_1	0.918350921123968	0.913032119384787
	r_2	0.604481122962660	0.720467822584888
	r_3	0.819032277069205	0.834132914830470
	r_4	0.909650581767270	0.933916908331804
	r_5	0.589440265509490	0.575828717398966
[5 5 4 3 3]	R_{system}	0.999862008622391	**0.999914090046997**
	r_1	.847427339971806	0.873517606218948
	r_2	0.802179306057867	0.666724644714909
	r_3	0.749865802726117	0.823244333397443
	r_4	0.962173945123998	0.963625603139065
	r_5	0.782178936779238	0.674757448125840
[5 2 2 6 2]	R_{system}	0.999858972183810	**0.999938777964879**
	r_1	0.863700128934150	0.877125082431281
	r_2	0.870379752584762	0.902449184112017
	r_3	0.928388104991992	0.948984803928944
	r_4	0.867818778271268	0.867012041915946
	r_5	0.800629701502485	0.796728615755417

Bold values mean the improved results

Table 6 Comparison of available resources for all redundancy levels

Redundancy level	Slack variable					
	Weight		Cost		Volume	
	GWO	HPSGWO	GWO	HPSGWO	GWO	HPSGWO
[4 3 3 4 4]	95	95	56.5044	**0.33415**	174.15	174.15
[4 4 5 2 3]	111	111	42.6589	**0.00734**	158.52	158.52
[4 4 4 4 4]	32	32	13.7760	**0.003478**	137.97	137.97
[5 5 4 3 3]	62	62	11.7713	**0.025524**	124.81	124.81
[5 2 2 6 2]	10	10	60.4677	**2.1204E-05**	153.58	153.58

Bold values mean the improved results

other redundancy levels for the system with a certain limit of weight and volume. The availability of these resources can comprise more redundant components that will directly affect the system's reliability proportionally. In view of Table 6, the system with redundancy level [5 2 2 6 2] has maximum weight, while the redundancy level [4 4 5 2 3] has minimum. Similarly, redundancy levels [5 5 4 3 3] and [4 3 3 4 4] have maximum and minimum volume, respectively, and the redundancy level [5 2 2 6 2] costs maximum to achieve the optimal reliability level, whereas the redundancy level [4 3 3 4 4] consumes minimum cost to achieve the global optimal reliability. All the above discussion indicates that for the FED, the first design with redundancy level [4 3 3 4 4] is the best choice for a system designer for a highly reliable and cost-efficient system.

9 Conclusion

This research work has examined an essential system FED for RRAP. For optimization purposes, a powerful meta-heuristic hybrid PSO–GWO is developed and a mixed-integer nonlinear programming problem is solved. Different levels of redundancies are considered for system design. The obtained outcomes profoundly help the system designers to create a system that is either highly reliable, cost-efficient, or less resource consumable. Also, the effectiveness of hybrid PSO–GWO is examined by testing it for all the CEC benchmark functions and comparing it with a triple hybrid algorithm.

In the future, more advanced and complex algorithms can be implemented to solve the proposed decision problem. Also, the proposed algorithm can be implemented for other challenging decision problems such as online learning, scheduling, multi-objective optimization, transportation, medicine, and data classification.

Author contributions The authors confirm contribution to the paper as follows: investigation and paper writing: ASB; writing and supervision: AK, MR. All authors reviewed the results and approved the final version of the manuscript.

Funding Not applicable.

Data availability Enquiries about data availability should be directed to the authors.

Declarations

Conflict of interest The authors declare that there is no conflict of interest regarding the publication of this paper.

Ethical approval Ethical approval is not applicable to this article.

Informed consent There are no human subjects in this article, and informed consent is not applicable.

References

Abouei Ardakan M, Zeinal Hamadani A (2014) Reliability optimization of series-parallel systems with mixed redundancy strategy in subsystems. Reliab Eng Syst Saf 130:132–139. https://doi.org/10.1016/j.ress.2014.06.001

Abouei Ardakan M, Sima M, Zeinal Hamadani A, Coit DW (2016) A novel strategy for redundant components in reliability–redundancy allocation problems. IIE Trans 48(11):1043–1057. https://doi.org/10.1080/0740817X.2016.1189631

Afonso LD, Mariani VC, dos Santos Coelho L (2013) Modified imperialist competitive algorithm based on attraction and repulsion concepts for reliability-redundancy optimization. Expert Syst Appl 40(9):3794–3802. https://doi.org/10.1016/j.eswa.2012.12.093

Ardakan MA, Hamadani AZ (2014) Reliability-redundancy allocation problem with cold-standby redundancy strategy. Simul Model Pract Theory 42:107–118. https://doi.org/10.1016/j.simpat.2013.12.013

Arezki Mellal M, Williams EJ (2018) Large-scale reliability-redundancy allocation optimization problem using three soft computing methods. In: Modeling and Simulation Based Analysis in Reliability Engineering, pp. 183–198. https://doi.org/10.1201/B22494-7

Bellman R, Dreyfus S (1958) Dynamic programming and the reliability of multicomponent devices. Oper Res 6(2):200–206. https://doi.org/10.1287/opre.6.2.200

Bhandari AS, Kumar A, Ram M (2022) Hybrid PSO-GWO algorithm for reliability redundancy allocation problem with Cold Standby Strategy. Qual Reliab Eng Int. https://doi.org/10.1002/QRE.3243

Bhandari AS, Kumar A, Ram M (2023) Grey wolf optimizer and hybrid PSO-GWO for reliability optimization and redundancy allocation problem. Qual Reliab Eng Int 39(3):905–921. https://doi.org/10.1002/QRE.3265

Boland PJ, El-Neweihi E, Proschan F (1992) Stochastic order for redundancy allocations in series and parallel systems. Adv Appl Probab 24(1):161–171. https://doi.org/10.2307/1427734

Chen TC (2006) IAs based approach for reliability redundancy allocation problems. Appl Math Comput 182(2):1556–1567. https://doi.org/10.1016/j.amc.2006.05.044

Chern MS (1992) On the computational complexity of reliability redundancy allocation in a series system. Oper Res Lett 11(5):309–315. https://doi.org/10.1016/0167-6377(92)90008-Q

da Costa Bueno V, do Carmo IM (2007) Active redundancy allocation for a k-out-of-n: F system of dependent components. Eur J Oper Res 176(2):1041–1051. https://doi.org/10.1016/j.ejor.2005.09.012

Dey B, Bhattacharyya B, Devarapalli R (2021) A novel hybrid algorithm for solving emerging electricity market pricing problem of microgrid. Int J Intell Syst 36(2):919–961. https://doi.org/10.1002/INT.22326

Dhillon A, Tyagi Y, Singh Bhandari A, Kumar A, Ram M (2022) Reliability redundancy allocation for hybrid electric vehicle using hybrid particle swarm Grey Wolf optimizer. Nonlinear Stud, Available www.nonlinearstudies.com

Dolatshahi-Zand A, Khalili-Damghani K (2015) Design of SCADA water resource management control center by a bi-objective redundancy allocation problem and particle swarm optimization. Reliab Eng Syst Saf 133:11–21. https://doi.org/10.1016/J.RESS.2014.07.020

Dulebenets MA (2021) An adaptive polyploid memetic algorithm for scheduling trucks at a cross-docking terminal. Inf Sci 565:390–421. https://doi.org/10.1016/J.INS.2021.02.039

Fouladi S, Safaei AA, Mammone N, Ghaderi F, Ebadi MJ (2022) Efficient deep neural networks for classification of Alzheimer's disease and mild cognitive impairment from Scalp EEG recordings. Cognit Comput 14(4):1247–1268. https://doi.org/10.1007/S12559-022-10033-3/METRICS

Fyffe DE, Hines WW, Lee NK (1968) System reliability allocation and a computational algorithm. IEEE Trans Reliab R-17(2):64–69. https://doi.org/10.1109/TR.1968.5217517

Garg H, Sharma SP (2013) Multi-objective reliability-redundancy allocation problem using particle swarm optimization. Comput Ind Eng 64(1):247–255. https://doi.org/10.1016/J.CIE.2012.09.015

Gen M, Yun YS (2006) Soft computing approach for reliability optimization: state-of-the-art survey. Reliab Eng Syst Saf 91(9):1008–1026. https://doi.org/10.1016/j.ress.2005.11.053

Hsieh YC, You PS (2011) An effective immune based two-phase approach for the optimal reliability—redundancy allocation problem. Appl Math Comput 218(4):1297–1307. https://doi.org/10.1016/J.AMC.2011.06.012

Hsieh YC, Chen TC, Bricker DL (1998) Genetic algorithms for reliability design problems. Microelectron Reliab 38(10):1599–1605. https://doi.org/10.1016/S0026-2714(98)00028-6

Kanagaraj G, Ponnambalam SG, Jawahar N (2013) A hybrid cuckoo search and genetic algorithm for reliability–redundancy allocation problems. Comput Ind Eng 66(4):1115–1124. https://doi.org/10.1016/J.CIE.2013.08.003

Kavoosi M et al (2020) Berth scheduling at marine container terminals: a universal island-based metaheuristic approach. Marit Bus Rev 5(1):30–66. https://doi.org/10.1108/MABR-08-2019-0032/FULL/PDF

Kennedy REJ (1995) Particle Swarm Optimization. In: Proceedings of the IEEE international conference on neural networks, IEEE, pp 1942–1948

Khalili-Damghani K, Abtahi AR, Tavana M (2013) A new multi-objective particle swarm optimization method for solving reliability redundancy allocation problems. Reliab Eng Syst Saf 111:58–75. https://doi.org/10.1016/J.RESS.2012.10.009

Kim H, Kim P (2017) Reliability–redundancy allocation problem considering optimal redundancy strategy using parallel genetic algorithm. Reliab Eng Syst Saf 159:153–160. https://doi.org/10.1016/j.ress.2016.10.033

Kim HG, Bae CO, Park DJ (2006) Reliability-redundancy optimization using simulated annealing algorithms. J Qual Maint Eng 12(4):354–363. https://doi.org/10.1108/13552510610705928

Kundu T, Garg H (2022) INNA: an improved neural network algorithm for solving reliability optimization problems. Neural Comput Appl 34(23):20865–20898. https://doi.org/10.1007/S00521-022-07565-Y/FIGURES/10

Li S, Chi X, Yu B (2022) An improved particle swarm optimization algorithm for the reliability–redundancy allocation problem with global reliability. Reliab Eng Syst Saf 225:108604. https://doi.org/10.1016/j.ress.2022.108604

Liang Q, Dong H, Yi X, Qin B, and Yang X (2017) A reliability optimization allocation method for multifunctional systems using new hybrid particle swarm optimization. In: Proceedings of 2016 11th International Conference on Reliability, Maintainability and Safety: Integrating Big Data, Improving Reliability and Serving Personalization, ICRMS 2016. https://doi.org/10.1109/ICRMS.2016.8050064

Luus R (1975) Optimization of system reliability by a new nonlinear integer programming procedure. IEEE Trans Reliab R-24(1):14–16. https://doi.org/10.1109/TR.1975.5215316

Mi J (1999) Optimal active redundancy allocation in k-out-of-n system. J Appl Probab 36(3):927–933. https://doi.org/10.1239/JAP/1032374645

Mirjalili S, Mirjalili SM, Lewis A (2014) Grey Wolf optimizer. Adv Eng Softw 69:46–61. https://doi.org/10.1016/j.advengsoft.2013.12.007

Nakagawa Y, Nakashima K (1977) A heuristic method for determining optimal reliability allocation. IEEE Trans Reliab R-26(3):156–161. https://doi.org/10.1109/TR.1977.5220101

Nam K, Mitsuo Gen H (1975) Reliability optimization by 0–1 programming for a system with several failure modes. IEEE Trans Reliab 24(3):206–210. https://doi.org/10.1109/TR.1975.5215154

Nazari K, Ebadi MJ, Berahmand K (2022) Diagnosis of Alternaria disease and leafminer pest on tomato leaves using image processing techniques. J Sci Food Agric 102(15):6907–6920. https://doi.org/10.1002/JSFA.12052

Rabbani M, Oladzad-Abbasabady N, Akbarian-Saravi N, Rabbani M, Oladzad-Abbasabady N, Akbarian-Saravi N (2022) Ambulance routing in disaster response considering variable patient condition: NSGA-II and MOPSO algorithms. J Ind Manag Optim 18(2):1035–1062. https://doi.org/10.3934/JIMO.2021007

Şenel FA, Gökçe F, Yüksel AS, Yiğit T (2019) A novel hybrid PSO–GWO algorithm for optimization problems. Eng Comput 35(4):1359–1373. https://doi.org/10.1007/s00366-018-0668-5

Shaked M, Shanthikumar JG (1992) Optimal allocation of resources to nodes of parallel and series systems. Adv Appl Probab 24(4):894–914. https://doi.org/10.2307/1427718

Sheikhalishahi M, Ebrahimipour V, Shiri H, Zaman H, Jeihoonian M (2013) A hybrid GA–PSO approach for reliability optimization in redundancy allocation problem. Int J Adv Manuf Technol 68(1):317–338. https://doi.org/10.1007/S00170-013-4730-6

Singh H, Singh RS (1997) Note: optimal allocation of resources to nodes of series systems with respect to failure-rate ordering. Naval Res Logist (NRL) 44(1):147–152

Tillman FA (1969) Optimization by integer programming of constrained reliability problems with several modes of failure. IEEE Trans Reliab R-18(2):47–53. https://doi.org/10.1109/TR.1969.5216977

Valian E, Valian E (2013) A cuckoo search algorithm by Lévy flights for solving reliability redundancy allocation problems. Eng Optim 45(11):1273–1286. https://doi.org/10.1080/0305215X.2012.729055

Wang L, Li LP (2012) A coevolutionary differential evolution with harmony search for reliability-redundancy optimization. Expert Syst Appl 39(5):5271–5278. https://doi.org/10.1016/j.eswa.2011.11.012

Wu P, Gao L, Zou D, Li S (2011) An improved particle swarm optimization algorithm for reliability problems. ISA Trans 50(1):71–81. https://doi.org/10.1016/j.isatra.2010.08.005

Yang XP, Kastenberg WE, Okrent D (1989) Optimal safety goal allocation for nuclear power plants. Reliab Eng Syst Saf 25(3):257–278. https://doi.org/10.1016/0951-8320(89)90096-3

Yang JE, Hwang MJ, Sung TY, Jin Y (1999) Application of genetic algorithm for reliability allocation in nuclear power plants. Reliab Eng Syst Saf 65(3):229–238. https://doi.org/10.1016/S0951-8320(98)00103-3

Yeh WC, Hsieh TJ (2011) Solving reliability redundancy allocation problems using an artificial bee colony algorithm. Comput Oper Res 38(11):1465–1473. https://doi.org/10.1016/j.cor.2010.10.028

Yeh WC, Lin JS (2018) New parallel swarm algorithm for smart sensor systems redundancy allocation problems in the Internet of Things. J Supercomput 74(9):4358–4384. https://doi.org/10.1007/S11227-016-1903-8/METRICS

Yokota T, Gen M, Li YX (1996) Genetic algorithm for non-linear mixed integer programming problems and its applications. Comput Ind Eng 30(4):905–917. https://doi.org/10.1016/0360-8352(96)00041-1

Zhang E, Chen Q (2016) Multi-objective reliability redundancy allocation in an interval environment using particle swarm optimization. Reliab Eng Syst Saf 145:83–92. https://doi.org/10.1016/J.RESS.2015.09.008

Zhang H, Sun M, Li YF (2022) Reliability–redundancy allocation problem in multi-state flow network: minimal cut-based approximation scheme. Reliab Eng Syst Saf 225:108564. https://doi.org/10.1016/J.RESS.2022.108564

Zou D, Gao L, Li S, Wu J (2011) An effective global harmony search algorithm for reliability problems. Expert Syst Appl 38(4):4642–4648. https://doi.org/10.1016/j.eswa.2010.09.120