Cost Optimization and Reliability Parameter Extraction of a Complex Engineering System

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Abstract

Nowadays, the transformation of the various energy system is the core objective of the dedicated sustainable development goal related to energy sustainable world within the new United Nations development agenda. Different nuclear regulatory authorities around the globe, sets Technical Specifications (TSs) for ensuring the human and environmental safety of various highly volatile and complex Nuclear Power Generation Plants (NPGPs). TSs define numerous measures and limitations related to safety and sustainability that must be followed by all NPGPs around the world. Reliability, availability and cost components associated with a NPGPs form important bases for the setting of TSs. In this work, a framework based on few recent metaheuristics like Cuckoo Search Algorithm (CSA), Grey Wolf Optimizer (GWO),

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Hybrid PSO GWO algorithm (HPSOGWO) has been presented for cost optimization and reliability parameter extraction of a complex engineering system named Heat Removal System (HRS) of a nuclear power generation plant safety system (NPGPSS). A multi-criteria decision-making (MCDM) method named Weighted-Sum Method (WSM) has also been employed for prioritizing the available metaheuristics based on available beneficial and non-beneficial criteria's.

Keywords: Reliability, cost, optimization, metaheuristics, heat removal system (HRS), nuclear power generation plants (NPGPs), weighted-sum method (WSM).

1 Introduction

For Development that fulfill the needs and wants of the present society without making any concession in the ability of upcoming generations to fulfil their own needs can be termed as Sustainable development. Since the 1992 United Nation (U.N.) Rio de Janeiro conference, Agenda 21, there have been a growing role of access to clean, reliable and sustainable energy for achieving sustainable development goals (SDGs) [1]. Nuclear power can be viewed as a suitable alternative to fossil fuels- the conventional energy sources for achieving a clean and sustainable environment along with a green economy. Nuclear reactors generate electricity in a nuclear power plant. NPGPs have complex subsystems and structures and any error whether it is human, mechanical or environmental can cause huge loss to society and the environment [2, 3]. Hence, nuclear regulatory authorities set TSs for ensuring well-being and safety of humankind and NPGPs [4, 5]. No industrial activity including power generation through NPGPs can be termed as completely risk-free. Few major accidents like Fukushima (Japan 2011), Chernobal (Ukraine 1986) etc. are most critical and devastating incidents of the past related to civil nuclear power generation which happened even after the presence of the auditor nuclear safety formed and recognized by United Nation (U.N) in 1957 “The International Atomic Energy Agency-IAEA” [6].

Due to the increasing quality consciousness among the customers, every industry has been focusing on developing tools and technology for enhancing the reliability of various components associated with various complex systems like NPGPs. In short, one can term reliability as “the probability that a system will work adequately for a reasonable period of time” [7]. The consequences of an unreliable complex system like NPGPs in terms of safety, human life, and environmental damage can be severe. Hence, it is essential for industries to strike a balance between system reliability and cost during the designing stage of such complex systems. Apart from that, to ensure the safety and reliability in the long-run of such a complex system, constantly huge investment is also needed for the maintenance and up-gradation.

In the past few decades, metaheuristics have become enormously popular amongst researchers of all communities due to their simple and derivation-free mechanism [8–11]. Problems related to the optimization of system reliability and reliability parameter extraction of complex systems like NPGPs are highly nonlinear optimization problems in nature and solutions to these NP-hard problems are quite complex even with moderate scale [12–15]. Conventional techniques of optimization fail in obtaining the global optimal solution for those NP- hard reliability optimization problems as they have nonlinearity associated with multiple local extreme values.

In metaheuristic algorithms, first the search space is exhaustively explored globally and then on the basis of some current suitable solution, an intensive local search which can be termed exploitation, is done further to obtain the best solution. Therefore, in any metaheuristic, a fine-tuning between these two processes is required [16, 17]. It is also worthy to notify "No Free Lunch theorem" here. As per this theorem, the suitability of any metaheuristics vary from problem to problem *i.e* for a particular problem where 'metaheuristic A' is giving promising results may give a poor performance on another set of problems [18]. The rest of the article has been structured as follows:

Section 2 provides a brief overview of various nature-inspired optimization techniques named CSA, GWO, HPSOGWO, and a MCDM method named WSM used for cost optimization, reliability parameter extraction, and prioritization in this article. Section 3 describes the nonlinear cost optimization problem related to the HRS of a NPGPSS. Numerical simulations and discussion are presented in Sections 4. In the last, results conclude in Section 5.

2 Materials and Methods

A set of novel techniques, which have drawn their origin from nature and use to solve complex and highly nonlinear optimization problems, can be termed nature-inspired optimization techniques. We first describe the nature-inspired optimization techniques and MCDM method used in this study.

2.1 System Cuckoo Search Algorithm (CSA)

Yang and Deb developed an evolutionary algorithm named cuckoo search algorithm (CSA) in the year 2009, which is motivated by the life of the Cuckoo-a bird [19].

The main behavioral aspect of cuckoo, which is the source of inspiration for this algorithm, is the brood parasites. Cuckoos follow brood parasites and they have a very aggressive reproduction strategy. They procreate in other-host net and remove the host's own eggs to increase the hatching probability of its own eggs.

Yang & Deb modeled the brood parasitism among cuckoos along with the concept of L´evy Flights by considering the three rules mentioned below [20, 21]:

1. A cuckoo chose nest randomly to dump its only egg.
2. Only those nests with best high quality of solutions (eggs) will carry forward.
3. The quantity of host nests available is fixed. p_a is the probability, lying between 0 and 1, that a host can identify an alien egg.

L´evy Flight for $x^{(t+1)}$ solution for cuckoo *i* is given by

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \bigoplus \rightleftarrows Levy(\lambda) \tag{1}$$

Where α denotes the step size and is greater than zero. CSA's pseudo code is presented in Figure 1.

Objective function $f(x)$, $x=(x_1, x_2, \ldots\ldots\ldots, x_d)^T$;

Initial a population of n host nests x_i $(i=1,2,\ldots\ldots\ldots,n)$;
while (t <MaxGeneration) or (stop criterion);
Get a cuckoo (say i) randomly by L´evy flights;
Evaluate its quality/fitness F_i;
Choose a nest among n (say j) randomly;
if ($F_i > F_j$),
Replace j by the new solution;
end
Abandon a fraction (p_a) of worse nests
[and build new ones at new locations via L´evy flights];
Keep the best solutions (or nests with quality solutions);
Rank the solutions and find the current best;
end while
Postprocess results and visualisation;

Figure 1 CSA's pseudo code.

2.2 Grey Wolf Optimizer (GWO)

Grey Wolf Optimizer (GWO) technique, which mimics the social behavior of wild animals named grey wolves (Canis lupus), is developed by Mirjalili et al. in year 2014 [22]. It mathematically modelled the social hierarchy and the hunting mechanism of grey wolves which used to live together in groups of 6–14 members. They categorize the whole pack of grey wolves, based on the social hierarchy, to four categories named alpha (α), beta (β), delta (δ) and omega (ω) wolves. Where, α holds the highest and ω kept at the lowest level in the social hierarchy. Apart from well structure social hierarchy they have well define mechanism of hunting which is mathematically define by the following equations:

$$\vec{D} = |\vec{C} \cdot \vec{Y}_P(t) - \vec{Y}(t)| \tag{2}$$

$$\vec{Y}(t+1) = \vec{Y}_P(t) - \vec{A} \cdot \vec{D} \tag{3}$$

Where $\vec{Y}_P$ denotes the prey's position vector and $\vec{Y}$ represent the position vector of a grey wolf. 't' define current iteration & the coefficient vectors $\vec{A}$ and $\vec{C}$ are given by the equations:

$$\vec{A} = 2\vec{a} \cdot \vec{s}_1 - \vec{a} \tag{4}$$

$$\vec{C} = 2 \cdot \vec{s}_2 \tag{5}$$

Where random vectors s_1 and s_2 are in $[0, 1]$ and during the iterations the component of $\vec{a}$ are decreasing linearly from 2 to 0.

It is also assumed that the α wolf (best candidate solution), β wolf and δ wolf have better understanding about the prey's location in comparison to ω wolf so that ω wolves to update their positions in accordance of α, β and δ wolf positions as per the below mentioned formulas as per the following formulas [22, 23]:

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{Y}_\alpha - \vec{Y}|, \quad \vec{D}_\beta = |\vec{C}_2 \vec{Y}_\beta - \vec{Y}|, \quad \vec{D}_\delta = |\vec{C}_3 \vec{Y}_\delta - \vec{Y}| \tag{6}$$

$$\vec{Y}_1 = \vec{Y}_\alpha - \vec{A}_1 \cdot (\vec{D}_\alpha), \quad \vec{Y}_2 = \vec{Y}_\beta - \vec{A}_2 \cdot (\vec{D}_\beta), \quad \vec{Y}_3 = \vec{Y}_\delta - \vec{A}_3 \cdot (\vec{D}_\delta) \tag{7}$$

$$\vec{Y}(t+1) = \frac{\vec{Y}_1 + \vec{Y}_2 + \vec{Y}_3}{3} \tag{8}$$

GWO's pseudo code is presented in Figure 2.

Initialize the grey wolf population $Y_i \ (i = 1, 2, \ldots\ldots\ldots, n)$
Initialize a, A and C
Calculate the fitness of each search agent
$\vec{Y}_\alpha$ = the best search agent
$\vec{Y}_\beta$ = the second best search agent
$\vec{Y}_\delta$ = the third best search agent

while (t < Max number of iterations)
  for each search agent
    Update the position of current search agent by equation (8)
end for
Update a, A, and C
Calculate the fitness of all search agents
Update $\vec{Y}_\alpha$ $\vec{Y}_\beta$ $\vec{Y}_\delta$
t = t+1
end while
return $\vec{Y}_\alpha$

Figure 2 GWO's pseudo code.

2.3 Hybrid PSO GWO Algorithm (HPSOGWO)

Hybridization of two metaheuristics can serve the purpose of obtaining the global best (g-best) solution much better than in comparison to individual metaheuristic in term of better quality solution, time and improved convergence rate etc. [24]. The purposes of hybridization of GWO with other metaheuristics are local maxima avoidance and the objective to get superior quality of g-best solution. One of most popular among them is the hybridization of particle swarm optimizer (PSO) with GWO named as hybrid PSO GWO technique (HPSOGWO) [25].

In the process of hybridization of PSO with GWO, the GWO play its role in the process of exploration whereas PSO strengthen the process of exploitation. Hence, ultimately strengthening the performance of HPSOGWO [26].

Original equations of GWO have been modified by using inertia weight constant w.

$$D_\alpha = |C_1 \cdot X_\alpha - w * X|; \quad D_\beta = |C_2 \cdot X_\beta - w * X|;$$
$$D_\delta = |C_3 \cdot X_\delta - w * X| \tag{9}$$

```
Initialization
Initialize l, a, w and c
// w = 0.5 + rand()/2
Evaluate the fitness of agents by using equation (9)
while (t < max no. of iter)
for each search agent
Update the velocity and position by using equation (10) & (11)
end for
Update l, a, w and c
Evaluate the fitness of all search agents
Update positon first three agents
t=t+1
end while
 return // first best search agent position
```

Figure 3 HPSOGWO's pseudo code.

The original equations of velocity and position of search agent in PSO are modified to the equations:

$$V_i^{k+1} = w * \{V_i^k + c_1 r_1 (x_1 - x_i^k) + c_2 r_2 (x_2 - x_i^k) + c_3 r_3 (3 - x_i^k)\} \tag{10}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{11}$$

HPSOGWO's pseudo code is presented in Figure 3.

2.4 Weighted Sum Method (WSM)

MCDM methods are used to select the best alternative amongst the set of available alternatives based on different multiple criteria, which may have different units [27].

First step of WSM is prioritization of the criteria's into beneficial and non-beneficial. beneficial criteria are the criteria whose greater value is desirable while non- beneficial are those whose lower value is desired [28]. Like reliability can be termed as beneficial and system cost can be viewed as non-beneficial criteria as one's desire to have a system with highest reliability and the lowest cost. After that normalization has to be done to make all criteria's comparable. In normalisation, the performance value of an individual cell has been divided by the maximum value in beneficial criteria. While, for non-beneficial criteria the performance value of an individual cell has been divided by the minimum value [29, 30].

$$\text{Non-Beneficial: } \frac{\min(x_{ij})}{x_{ij}}, \quad \text{Beneficial: } \frac{x_{ij}}{Max(x_{ij})} \tag{12}$$

By following a normalized decision matrix can be obtain. Next step of WSM is to assign the weightage to the criteria. Here, we have consider that the equal weightage i.e. 0.25 weightage have been allotted to each of the criteria. After that multiply the weightage assigned to every criteria with it's normalised performance value. By doing so, we get weighted normalised decision matrix.

$$A_i = \sum_{i=1}^{n} w_j \, x_{ij} \tag{13}$$

Next, one can add all weighted normalized performance value of every alternative to get a performance score. Now, ranks can be allocated to various nature-inspired optimization algorithms based on the performance score.

3 Problem Description

The main task of quality and reliability engineers is to deal with various complex systems having a mixed configuration, i.e. the sub-system associated are purely connected neither in series nor in a parallel. Here such a highly complex system named HRS of a NPGPSS is taken into consideration for cost Optimization and reliability parameter extraction by using few recent metaheuristics.

Here, in this robust and complex design of a NPGPSS, the emergency core-cooling subsystem of a nuclear power generation reactor consist of a core flooding system, which has low pressure. Hence, it become mandatory to have a heat removing system associated with it [31]. This low-pressure heat removing system directly connected with another high-pressure system. The main purpose of this HRS is the removal of residual heat at the time of maintenance, servicing and refueling of reactor. Here, Figure 4 represent the schematic of the system [4, 6].

The reliability of the HRS of a NPGPSS is given by $R_{sys.}$ where

$$\begin{aligned}
R_{sys.} = {} & (1-r_1)(1-r_3)(1-r_5) + (1-r_1)(1-r_3)(1-r_6)r_5 \\
& + (1-r_1)(1-r_3)(1-r_7)r_5r_6 \\
& + (1-r_1)(1-r_3)(1-r_8)r_5r_6r_7 \\
& + (1-r_1)(1-r_4)(1-r_5)r_3 + (1-r_1)(1-r_4)(1-r_6)r_3r_5 \\
& + (1-r_1)(1-r_4)(1-r_7)r_3r_5r_6 \\
& + (1-r_1)(1-r_4)(1-r_8)r_3r_5r_6r_7 \\
& + (1-r_2)(1-r_3)(1-r_5)r_1 + (1-r_2)(1-r_3)(1-r_6)r_1r_5 \\
& + (1-r_2)(1-r_3)(1-r_7)r_1r_5r_6 \\
& + (1-r_2)(1-r_3)(1-r_8)r_1r_5r_6r_7 \\
& + (1-r_2)(1-r_4)(1-r_5)r_1r_3 \\
& + (1-r_2)(1-r_4)(1-r_6)r_1r_3r_5 \\
& + (1-r_2)(1-r_4)(1-r_7)r_1r_3r_5r_6 \\
& + (1-r_2)(1-r_4)(1-r_8)r_1r_3r_5r_6r_7 \qquad (14)
\end{aligned}$$

And the relation between system reliability $R_{Sys.}$ and system reliability $Q_{Sys.}$ is given by

$$R_{Sys.} = 1 - Q_{Sys.} \qquad (15)$$

Where q_i represents unreliability and $1 - q_i = r_i$ denotes the reliability of the i^{th} component. Furthermore, the system cost $C_{Sys.}$ is given by the equation

$$C_{Sys.} = 2\sum_{i=1}^{8} K_i r_i^{\alpha_i} \qquad (16)$$

$C_{Sys.}$ is a combination of components reliabilities which are nonlinear in nature. This combination is taken from the system design point of view as it seeks to place a constrain on $C_{Sys.}$ [32].

Here $K_1 = K_2 = K_3 = K_5 = K_6 = K_7 = K_8 = 100$ and $K_4 = 150$ and α_i is 0.6 for all ‘i’.

In the framework proposed here, the system cost $C_{Sys.}$ with various inequality constraints based on reliability parameters has been considered as an objective function, which has to be minimized. This leads to a single-objective optimization problem, which is highly nonlinear in nature.

Minimize system cost $(C_{Sys.})$

Subjected to

$$0.5 \leq r_i \leq 1 \quad \forall i$$

$$0.9 \leq R_{Sys.} \leq 1$$

4 Numerical Simulations and Discussion

Nowadays various researchers are using metaheuristics for getting the solution of various real life complex nonlinear optimization problems [33–37]. Here, for the above mentioned problem of cost optimization and reliability parameter extraction of HRS of a NPGPSS, the simplest constraints handling method named penalty functions have been used and few recent metaheuristics namely CSA, GWO, HPSOGWO have been employed in MATLAB. The best results obtain by those metaheuristics are demonstrated in Table 1.

For the above-mentioned problem, in CSA the Number of nests are fixed as 30 considering the discovery rate of alien eggs (solutions) as 0.25. CSA has been executed in MATLAB for 500 iterations. On the other hand, for GWO the number of initial population of wolves have been set at 100 and the algorithm run for 300 iterations in MATLAB. Figure 5 presents the search history (GWO) for HRS of a NPGPSS.

Table 1 Comparison results for HRS of a NPGPSS

Comparison Results for HRS of a NPGPSS			
Optimum Variables/Algorithm	CSA	GWO	HPSOGWO
r_1	0.925926	0.921610	0.919034
r_2	0.926399	0.930850	0.934140
r_3	0.500000	0.500180	0.500000
r_4	0.500000	0.500000	0.500000
r_5	0.500000	0.500000	0.500000
r_6	0.500000	0.500000	0.500000
r_7	0.500000	0.500000	0.500000
r_8	0.500000	0.500000	0.500000
Optimum $C_{Sys.}$	1305.663570	1305.707000	1305.765450
Optimum $R_{Sys.}$	0.999666	0.999667	0.999673
Number of Iterations	500	300	500
Function Evaluated FE	30000	30000	15000

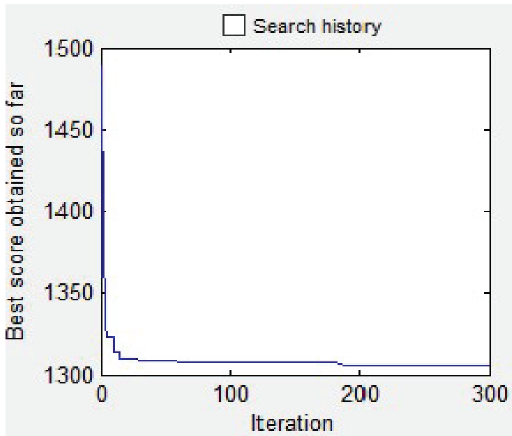

Figure 5 Search history (GWO) for HRS of a NPGPSS.

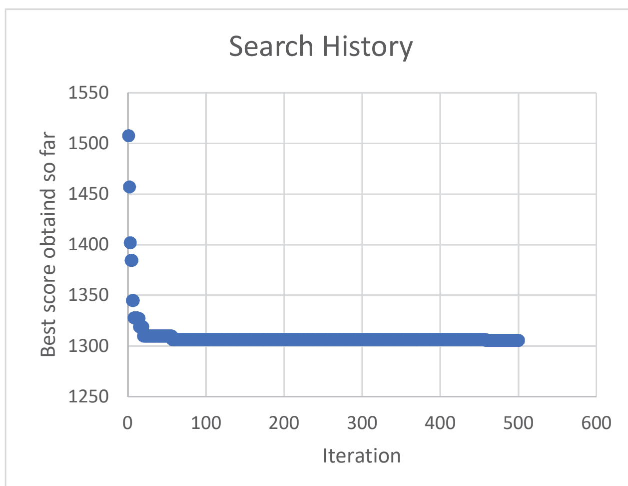

Figure 6 Search history (HPSOGWO) for HRS of a NPGPSS.

For HPSOGWO the number of search agent is fixed at 30 and the algorithm is run for 500 iteration in MATLAB. Search history by HPSOGWO for HRS of a NPGPSS is depicted in Figure 6.

Table 1 shows that CSA provides minimum system cost 1305.663570 with 0.999666 system reliability while HPSOGWO provides system cost 1305.765450 with 0.999673 system reliability. Total number of FE for GWO and CSA are 30000 and total number of FE for HPSOGWO are 15000.

Table 2 Classification of available criteria's into beneficial and non-beneficial

Classification of Available Criteria's	Non-Beneficial	Beneficial	Non-Beneficial	Non-Beneficial
Alternatives/ Criteria's	$C_{Sys.}$	$R_{Sys.}$	Number of Iterations	Function Evaluated FE
CSA	1305.663570	0.999666	500	30000
GWO	1305.707000	0.999667	300	30000
HPSOGWO	1305.765450	0.999673	500	15000

Table 3 Normalized decision matrix and performance score of all available alternatives by WSM

	Normalized Decision Matrix					
Alternatives/ Criteria's	$C_{Sys.}$	$R_{Sys.}$	Number of Iterations	Function Evaluated FE	Performance Score	Priority
CSA	1	0.999993	0.6	0.5	0.774998	3
GWO	0.999967	0.999994	1	0.5	0.874990	2
HPSOGWO	0.999922	1	0.6	1	0.899980	1

For the purpose of prioritization of various metaheuristics used in the solution of this highly nonlinear optimization problem and for the employment of weightage sum method, system reliability $C_{Sys.}$, system cost $R_{Sys.}$, number of iterations and function evaluated have been considered as various available criteria's. Classification of these available Criteria's into beneficial and non-beneficial have been done in Table 2.

Here, the equal weightage i.e. 0.25 weightage have been allotted to each of the criteria and the performance score along with the priority by WSM method is reported in Table 3.

5 Conclusion

In this work, a framework based on few recent metaheuristics and a MCDM method named WSM has implemented for cost optimization and reliability parameter extraction of HRS of a NPGPSS. A vital practical application of metaheuristics and a MCDM method in optimizing the TSs of nuclear power generation plant safety system has been demonstrated. An efficient strategy based on WSM for prioritizing the metaheuristics used for decision maker have been presented so that he/she can prioritize the methods of his/her interest. Furthermore, it is evident from the study that the result obtained by HPSOGWO are superior to the results that have been obtained by CSA, GWO. Therefore, it can be concluded that the combination of metaheuristics along with MCDM techniques can provide solutions to various complex problems related to energy system so they can play vital role for achieving the sustainable development goal related to energy sustainable world within the new United Nations development agenda.

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