

## RESEARCH ARTICLE

# Cost minimization of repairable systems subject to availability constraints using efficient cuckoo optimization algorithm

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## Abstract

System availability is a key element for any industry. System designers and operators try to do their best to maintain the required availability of the systems to avoid production stoppages. They set up and undertake different maintenances, and these interventions imply cost. Therefore, the goal is to minimize the cost, but considering the constraint of the availability requirement. The problem involves three main aspects: redundancy allocation, component failure rates, and repair rates. In this paper, a novel solution approach is proposed based on an efficient cuckoo optimization algorithm (EF-COA). Two numerical case studies are solved, and the results confirm the effectiveness of the approach proposed.

## KEYWORDS

availability requirement, efficient cuckoo optimization algorithm (EF-COA), repairable systems, system cost

## 1 | INTRODUCTION

A competitive industrial plant or infrastructure requires a highly dependable system with minimum functioning cost. The system dependability is a challenge that simultaneously incorporates reliability, availability, maintainability, and safety (RAMS).<sup>1</sup> The focus of the designer depends on the target, criteria, and system nature, such as nuclear power plants<sup>2,3</sup> and network systems (eg, electric power transmission/distribution systems, water/oil/gas distribution systems, computer/communication systems, and rail/road transportation systems).<sup>4</sup>

Higher RAMS allocation improves system dependability but also increases system cost.<sup>5</sup> Most of RAMS problems are described as optimization problems with single or multi objective functions subject to the constraints fixed by the specifications (eg, weight and volume). Evolutionary computation methods, also referred to artificial intelligence methods (AI), have successfully dealt with RAMS problems. In previous studies,<sup>6–13</sup> the authors used the artificial bee colony (ABC)<sup>6</sup>, immune based algorithm (IA)<sup>7</sup>, differential evolution with Lévy flight (DE)<sup>8</sup>, the biogeography-based optimization algorithm (BBO)<sup>9</sup>, particle swarm optimization (PSO)<sup>10,11</sup>, penalty guided stochastic fractal search<sup>12</sup>, and the gray wolf optimizer algorithm<sup>13</sup> for system reliability models. In Marseguerra et al,<sup>1</sup> a multi-objective approach

based on genetic algorithm has been presented for simultaneously dealing with the following objectives: system reliability, system maintainability, system safety, and cost (RAMS&C). In Liu,<sup>14,15</sup> a method was proposed combining Tabu search and genetic algorithm (TA-GA) for minimizing the system cost under availability constraint. An ant algorithm for single and multi-objective system reliability problem has been developed in Shelokar et al.<sup>16</sup> Recently, three evolutionary computation methods have been applied to a pharmaceutical plant in order to increase the overall system reliability<sup>17</sup>. The maintainability of a system by considering the failure and repair processes has been investigated in Cha and Finkelstein,<sup>18</sup> whereas a new mathematical model of reliability for multi-state degraded repairable system has been proposed in Yu et al.<sup>19</sup>

The great challenge is to effectively deal with the dependability of the system and improve its elements. In this paper, we propose a novel solution approach for minimizing the system cost under system availability constraints, by resorting to a modification of the basic cuckoo optimization algorithm (COA)<sup>20</sup>, in the present work called efficient cuckoo optimization algorithm (EF-COA). The remainder of the paper is organized as follows. Section 2 describes the system cost minimization problem subject to availability constraint. Section 3 presents the schemes of the EF-COA. In Section 4, two numerical case studies are presented. Finally, conclusions are drawn at closure.

## 2 | PROBLEM DESCRIPTION

The general mathematical formulation of the considered cost minimization problem of repairable systems is given as follows<sup>14,15</sup>:

$$\text{Minimize } C_S(n, \lambda, \mu) = C_S(n_1, n_2, \dots, n_m; \lambda_1, \lambda_2, \dots, \lambda_m; \mu_1, \mu_2, \dots, \mu_m), \quad (1)$$

where  $C_S(\bullet)$  is the total system cost,  $n_i$  is the number of redundant components in the  $i$ th subsystem,  $\lambda_i$  is the failure rate of the components in the  $i$ th subsystem, and  $\mu_i$  is the repair rate of the components in the  $i$ th subsystem,

subject to

$$g_j(n_1, n_2, \dots, n_m) \leq b, \quad (2)$$

$$A_S(n, \lambda, \mu) \geq A_S^*, \quad (3)$$

$$\begin{aligned} n_i &\geq 1; n_i \in \mathbb{Z}^+ \\ \lambda_i &\in [\lambda_{iL}, \lambda_{iU}] \subset \mathfrak{R}^+ \\ \mu_i &\in [\mu_{iL}, \mu_{iU}] \subset \mathfrak{R}^+, \\ i &= 1, 2, \dots, m, \end{aligned}$$

where  $g(\bullet)$  is the set of constraints,  $b$  is the vector of resource limitation,  $A_S(\bullet)$  is the system availability,  $A_S^*$  is the system availability requirement, and  $m$  is the number of subsystems in the system.

## 3 | EFFICIENT COA

The COA is a bio-inspired evolutionary optimization method developed by Rajabioun.<sup>20</sup> The basic principles are based on the lifestyle and behavior of the birds, cuckoos, for their reproduction. Several works available in the literature used the main concepts of this algorithm for solving various engineering problems, such as multivariable controller design<sup>20</sup>, replacement of obsolete components in industrial plants<sup>21,22</sup>, data clustering<sup>23</sup>, machining parameters<sup>24-26</sup>, job scheduling<sup>27</sup>, warranty period definition<sup>28</sup>, nonconvex combined heat and power economic dispatch<sup>29</sup>, and recognition of control chart patterns<sup>30</sup>. The standard COA implies the major steps reported in Appendix A.<sup>20</sup>

To effectively solve the system cost minimization subject to the availability constraint described in Section 2, the basic COA is improved for better performance and the new approach is called EF-COA. The new steps of the algorithm are described as follows:



All the nests of each habitat are classified and the best one is identified. The worst nests in each habitat mean that the eggs were recognized by the host birds and have been destroyed. Therefore, the best habitat includes the identified best nest (minimum system cost) and implies that this habitat represents the migration target for the cuckoo as follows:

$$Habitat_{Best} = \{Nest_{Best}\} = C_{S_{Best}}(n, \lambda, \mu) = C_{S_{Best}}(n_1, n_2, \dots, n_m, \lambda_1, \lambda_2, \dots, \lambda_m, \mu_1, \mu_2, \dots, \mu_m), \quad (7)$$

where  $Habitat_{Best}$  is the best habitat with the best  $Nest_{Best}$ .

Step 5. Use the best solution of the last previous cuckoo's generation (iteration) in the next one.

The best nest (best solution) of the last previous cuckoo's generation (ie, iteration) is considered a fixed nest for each habitat in the current iteration and the remaining nests are randomly generated. This step improves the solution's quality from one iteration to the next as follows:

$$\left( \begin{array}{l} Habitat_1 = \left\{ \begin{array}{l} Nest_{Best} = C_{S_{Best}}(n, \lambda, \mu) = C_{S_{Best}}(n_1, n_2, \dots, n_m, \lambda_1, \lambda_2, \dots, \lambda_m, \mu_1, \mu_2, \dots, \mu_m) \\ Nest_{2,1} = C_{S_{2,1}}(n, \lambda, \mu) = C_{S_{2,1}}(n_1, n_2, \dots, n_m, \lambda_1, \lambda_2, \dots, \lambda_m, \mu_1, \mu_2, \dots, \mu_m) \\ \vdots \\ Nest_{k_1,1} = C_{S_{k_1,1}}(n, \lambda, \mu) = C_{S_{k_1,1}}(n_1, n_2, \dots, n_m, \lambda_1, \lambda_2, \dots, \lambda_m, \mu_1, \mu_2, \dots, \mu_m) \end{array} \right. \\ \\ Habitat_2 = \left\{ \begin{array}{l} Nest_{Best} = C_{S_{Best}}(n, \lambda, \mu) = C_{S_{Best}}(n_1, n_2, \dots, n_m, \lambda_1, \lambda_2, \dots, \lambda_m, \mu_1, \mu_2, \dots, \mu_m) \\ Nest_{2,2} = C_{S_{2,2}}(n, \lambda, \mu) = C_{S_{2,2}}(n_1, n_2, \dots, n_m, \lambda_1, \lambda_2, \dots, \lambda_m, \mu_1, \mu_2, \dots, \mu_m) \\ \vdots \\ Nest_{k_2,2} = C_{S_{k_2,2}}(n, \lambda, \mu) = C_{S_{k_2,2}}(n_1, n_2, \dots, n_m, \lambda_1, \lambda_2, \dots, \lambda_m, \mu_1, \mu_2, \dots, \mu_m) \end{array} \right. \\ \\ \vdots \\ \\ Habitat_H = \left\{ \begin{array}{l} Nest_{Best} = C_{S_{Best}}(n, \lambda, \mu) = C_{S_{Best}}(n_1, n_2, \dots, n_m, \lambda_1, \lambda_2, \dots, \lambda_m, \mu_1, \mu_2, \dots, \mu_m) \\ Nest_{2,H} = C_{S_{2,H}}(n, \lambda, \mu) = C_{S_{2,H}}(n_1, n_2, \dots, n_m, \lambda_1, \lambda_2, \dots, \lambda_m, \mu_1, \mu_2, \dots, \mu_m) \\ \vdots \\ Nest_{k_H,H} = C_{S_{k_H,H}}(n, \lambda, \mu) = C_{S_{k_H,H}}(n_1, n_2, \dots, n_m, \lambda_1, \lambda_2, \dots, \lambda_m, \mu_1, \mu_2, \dots, \mu_m) \end{array} \right. \end{array} \right) \quad (8)$$

$$k_1, k_2, \dots, k_H \in \{2, 3, 4, \dots, K\}.$$

Step 6. Steps 2 to 5 are repeated for a fixed number of iterations; then, the minimum system cost with the optimal values are displayed.

The pseudo-code of the developed EF-COA for the cost minimization of repairable systems subject to availability constraint is presented in Algorithm 1, and Figure 1 shows its flowchart.

## 4 | CASE STUDIES

### 4.1 | Parallel-series system

The overall system cost of five subsystems connected in parallel-series configuration (see Figure 2) is given by the mathematical model<sup>14</sup> as follows:

$$\text{Minimize } C_s(n, \lambda, \mu) = \sum_{i=1}^5 \left[ \left( \alpha_i (\lambda_i)^{-\beta_i} + \mu_i m c_i \right) (n_i + \exp(n_i/4)) \right]. \quad (9)$$

Subject to

$$\sum_{i=1}^5 p_i (n_i)^2 \leq 150, \quad (10)$$

$$\sum_{i=1}^5 w_i n_i \exp(n_i/4) \leq 200, \quad (11)$$

$$\prod_{i=1}^5 \left[ 1 - \left( 1 - \frac{\mu_i}{\lambda_i + \mu_i} \right)^{n_i} \right] \geq 0.9, \quad (12)$$

$$n_i \geq 1; n_i \in \mathbb{Z}^+$$

$$\lambda_i \in [10^{-7}, 10^{-3}] \subset \mathfrak{R}^+$$

$$\mu_i \in [32 \times 10^{-7}, 32 \times 10^{-3}] \subset \mathfrak{R}^+$$

$$i = 1, 2, \dots, 5,$$

where Equation (10) is the system design configuration constraint of weight, Equation (11) is the system design configuration constraint of the product of weight and volume, and Equation (12) is the system availability requirement constraint. The above problem involves five integer variables and 10 real variables. Table 1 reports the relevant data.

## 4.2 | *n*-stage standby system

The *n*-stage standby system considered includes five subsystems<sup>15</sup> (see Figure 3), and the corresponding optimization reads:

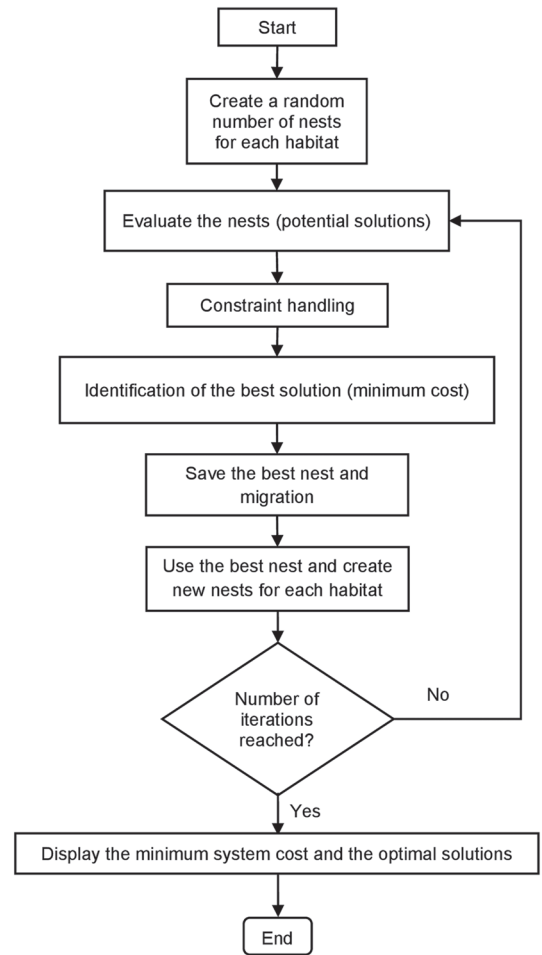
$$\text{Minimize } C_s(n, \lambda, \mu) = \sum_{i=1}^5 \left[ \left( \alpha_i (\lambda_i)^{-\beta_i} + \mu_i m c_i \right) (n_i + \exp(n_i/4)) \right]. \quad (13)$$

### ALGORITHM 1

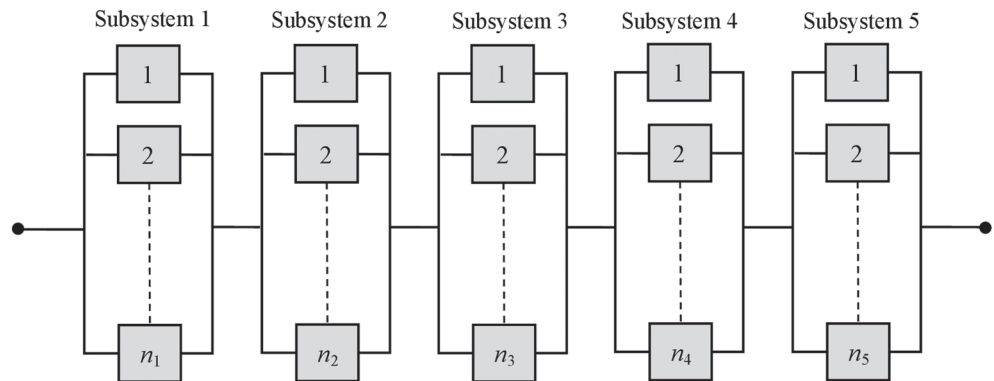
#### Pseudo-code of the implemented EF-COA.

1. Input the parameters:  $H, K, \Omega, \Phi_j, N_{Iter}$ .
2. Generate random number of nests for each habitat according to Equation (4).
3. While  $G \leq N_{Iter}$
4. Evaluate the system cost (each nest) according to Equation (5).
5. Constraint handling using Equation (6).
6. Identify the best solution (minimum system cost) and migration (save this best solution) according to Equation (7).
7. Use the saved solution to create new habitats and nests according to Equation (8).
9. End while
10. Display the minimum system cost and the optimal values.

**FIGURE 1** Flowchart of the implemented efficient cuckoo optimization algorithm (EF-COA)

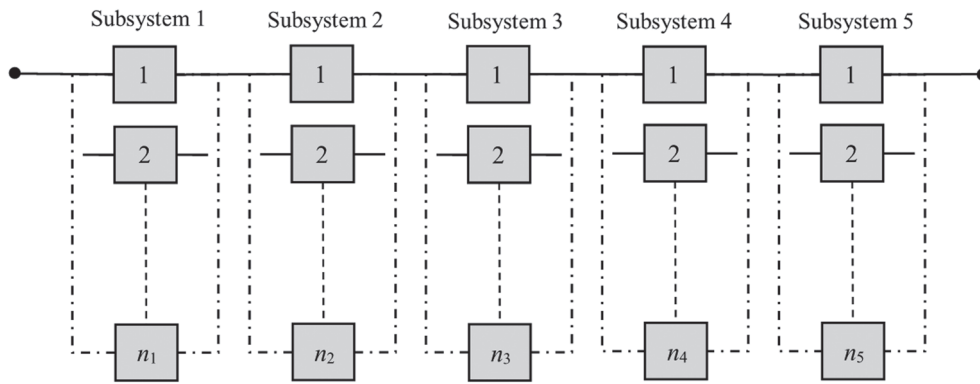


**FIGURE 2** Parallel-series system



**TABLE 1** Data used in parallel-series and *n*-stage standby systems

Subsystem <i>i</i>	$\alpha_i (10^{-5})$	$\beta_i$	$mc_i$	$p_i$	$w_i$
1	2.33	1.5	5000	1	7
2	1.45	1.5	5000	2	8
3	0.541	1.5	5000	3	8
4	8.05	1.5	5000	4	6
5	1.95	1.5	5000	2	9



**FIGURE 3**  $n$ -stage standby system

Subject to

$$\sum_{i=1}^5 p_i(n_i)^2 \leq 150, \quad (14)$$

$$\sum_{i=1}^5 w_i n_i \exp(n_i/4) \leq 200, \quad (15)$$

$$\prod_{i=1}^5 \left[ 1 - \left( \sum_{k=0}^{n_i} \left( \frac{\lambda_i}{\mu_i} \right)^k \right)^{-1} \left( \frac{\lambda_i}{\mu_i} \right)^{n_i} \right] \geq 0.9, \quad (16)$$

$$n_i \geq 1; n_i \in \mathbb{Z}^+$$

$$\lambda_i \in [10^{-7}, 10^{-3}] \subset \mathfrak{R}^+$$

$$\mu_i \in [32 \times 10^{-7}, 32 \times 10^{-3}] \subset \mathfrak{R}^+$$

$$i = 1, 2, \dots, 5.$$

The data and the constraints (14) and (15) are the same as for the parallel-series system. However, the system availability requirement constraint formulated in Equation (16) is more complex than that in Equation (12).

## 5 | RESULTS AND DISCUSSION

The developed EF-COA has been coded using the MATLAB programming language and run on a personal computer with a Processor G620 (2.60 GHz Sandy Bridge, 4 GB of RAM and 3 Mo of cache memory) under the Windows 7 to 64bits operating system. The number of habitats and the maximum number of nests per habitat is 10. The number of iterations is fixed at 50, ie, the maximum number of function evaluations that the algorithm may use is 5000. The base COA has been also applied to compare the results.

Tables 2 and 3 report the results for the two case studies. The best values of the system cost and number of function evaluations (NFE) are highlighted in bold. In Table 2, the cost obtained by the EF-COA for the parallel-series system is 214.1934 (in arbitrary cost units), which is smaller than that of COA (214.2662) and TA-GA (214.7794).<sup>14</sup> The EF-COA also used the lowest NFE (5000) compared with the other methods, 30 000 and 40 000, respectively. From Table 3, it can be observed that the cost provided by the EF-COA (234.9172) for the  $n$ -stage standby system is less than the result of the TA-GA (236.8314)<sup>15</sup> and the COA (236.2035). The NFE performance is also better, as for the parallel-series system. Furthermore, the standard deviations (SDs) of 20 independent runs reveal that the EF-COA is more stable than the COA, ie, smaller SD.

Figures 4–6 highlight the performances of the proposed EF-COA for the parallel-series system and the  $n$ -stage standby system, respectively.

**TABLE 2** Results for the parallel-series system

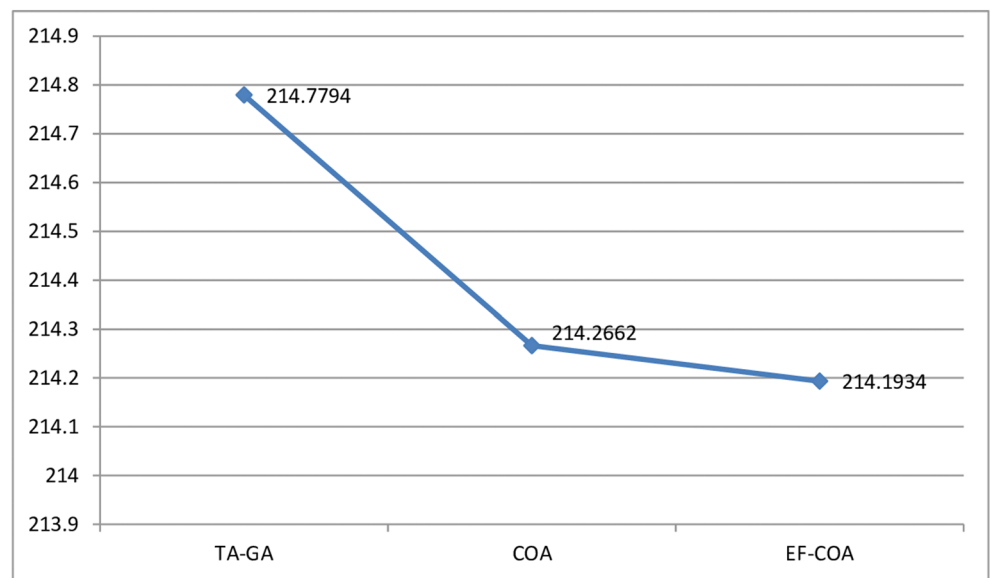
Method	$n$	$\lambda (10^{-3})$	$\mu (10^{-2})$	$A$	$A_s$	$C_s$	NFE	SD
TA-GA <sup>14</sup>	(3, 2, 2, 3, 3)	(0.3584, 0.2236, 0.1447, 0.6568, 0.3401)	(0.10, 0.14, 0.09, 0.15, 0.09)	(0.9830, 0.9802, 0.9812, 0.9726, 0.9789)	0.9000	214.7794	40,000	-
COA	(3, 2, 2, 3, 3)	(0.3640, 0.2307, 0.1466, 0.6469, 0.3419)	(0.1018, 0.1317, 0.0999, 0.1449, 0.0965)	(0.9817, 0.9777, 0.9836, 0.9705, 0.9820)	0.9000	214.2662	30,000	6.32E-03
<b>EF-COA (proposed approach)</b>	(3, 2, 2, 3, 3)	(0.3636, 0.2249, 0.1425, 0.6494, 0.3360)	(0.1004, 0.1283, 0.0972, 0.1463, 0.0952)	(0.9812, 0.9777, 0.9836, 0.9709, 0.9822)	0.9000	<b>214.1934</b>	<b>5,000</b>	<b>4.29E-05</b>

Abbreviations: EF-COA, efficient cuckoo optimization algorithm; NFE, number of function evaluations; SD, standard deviation; TA-GA, Tabu search and genetic algorithm. Bold values represent the best results.

**TABLE 3** Results for the  $n$ -stage standby system

Method	$n$	$\lambda (10^{-3})$	$\mu (10^{-2})$	$A$	$A_s$	$C_s$	NFE	SD
TA-GA <sup>15</sup>	(3, 3, 2, 3, 2)	(0.3261, 0.2749, 0.1507, 0.5963, 0.2555)	(0.12, 0.10, 0.10, 0.17, 0.15)	(0.9852, 0.9838, 0.9808, 0.9710, 0.9750)	0.9000	236.8314	40,000	-
COA	(2, 3, 2, 3, 3)	(0.2737, 0.2712, 0.1382, 0.5901, 0.3106)	(0.1548, 0.0970, 0.0998, 0.1685, 0.1068)	(0.9741, 0.9841, 0.9834, 0.9716, 0.9824)	0.9000	236.2035	30,000	5.17E-02
<b>EF-COA (proposed approach)</b>	(3, 3, 3, 2, 2)	(0.3329, 0.2694, 0.1653, 0.4893, 0.2486)	(0.1133, 0.0972, 0.0672, 0.2288, 0.1502)	(0.9819, 0.9845, 0.9887, 0.9636, 0.9770)	0.9000	<b>234.9172</b>	<b>5,000</b>	<b>7.04E-04</b>

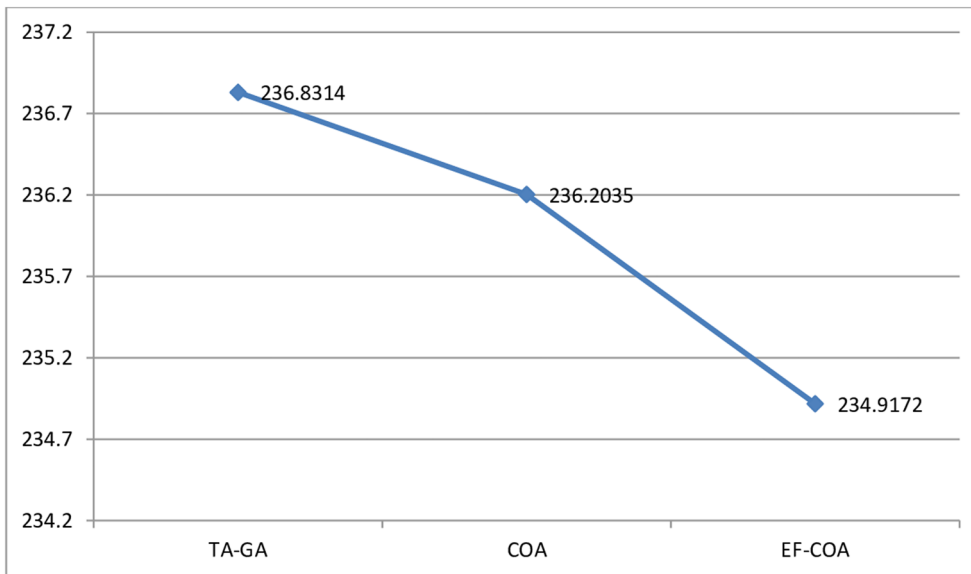
Abbreviations: EF-COA, efficient cuckoo optimization algorithm; NFE, number of function evaluations; SD, standard deviation; TA-GA, Tabu search and genetic algorithm. Bold values represent the best results.



**FIGURE 4** System cost for the parallel-series system [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

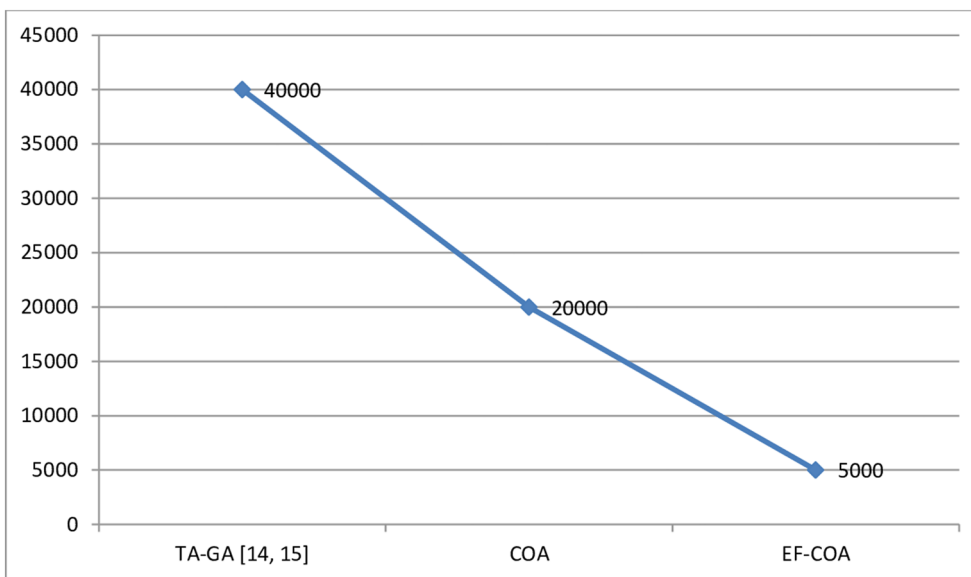
TA-GA<sup>14</sup>





**FIGURE 5** System cost for the  $n$ -stage standby system [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

TA-GA<sup>15</sup>



**FIGURE 6** Number of function evaluations (NFE) for the parallel-series system and the  $n$ -stage standby system [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

TA-GA<sup>14, 15</sup>

## 6 | CONCLUSIONS

In this paper, a new solution approach for minimizing the system cost of repairable systems subject to availability constraints has been proposed. A novel method based on the habitats and floating nests of the cuckoo, called the EF-COA, has been developed. The standard COA uses the egg-laying radius (ELR), which may slow down the algorithm when solving a complex problem. In the EF-COA, various habitats consisting of different nests are implemented in order to improve the quality on the solution and the performances. Therefore, the ELR has been avoided, while the system cost has been modeled as a nest. Application to two numerical case studies, ie, parallel-series system and  $n$ -stage standby system, has demonstrated the effectiveness of the proposed method in terms of better solutions and fewer function evaluations. Future research efforts will be devoted to extending the method for treating and addressing multi-objective optimization problems and a comprehensive industrial case study.

## NOMENCLATURE

$A$	$=(A_1, A_2, \dots, A_m)$ , vector of component availabilities for the system
$A_i$	availability of each component in subsystem $i$ , $1 \leq i \leq m$
$A_S$	system availability
$A_S^*$	system availability requirement
$b$	vector of resource limitation
$g_j$	$j$ th constraint function, $j = 1, \dots, M$
$m$	number of subsystems in the system
$M$	number of constraints
$n$	$=(n_1, n_2, \dots, n_m)$ , vector of redundancy allocation for the system
$n_i$	number of components in subsystem $i$ , $1 \leq i \leq m$
$P$	limitation on product of weight and volume
$R_i$	$= 1 - (1 - r_i)^{n_i}$ , reliability of the $i$ th subsystem, $1 \leq i \leq m$
$T$	operating time during which the component must not fail (mission time, $T = 1000$ )
$w_i$	weight of each component in subsystem $i$ , $1 \leq i \leq m$
$\beta_i, \alpha_i$	parameters representing physical features (shaping and scaling factors, respectively) of each component at subsystem $i$ , $1 \leq i \leq m$
$\mu$	$=(\mu_1, \mu_2, \dots, \mu_m)$ , vector of component repair rates for the system
$\mu_i$	repair rate of each component in subsystem $i$ , $1 \leq i \leq m$
$\lambda$	$=(\lambda_1, \lambda_2, \dots, \lambda_m)$ , vector of component failure rates for the system
$\lambda_i$	failure rate of each component in subsystem $i$ , $1 \leq i \leq m$
$\lambda_{iL}, \mu_{iL}$	lower limits on the failure rate and repair rate of each component in subsystem $i$ , $1 \leq i \leq m$
$\lambda_{iU}, \mu_{iU}$	upper limits on the failure rate and repair rate of each component in subsystem $i$ , $1 \leq i \leq m$

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**APPENDIX A.**

Step 1. Generate initial cuckoo habitat.

The initial set of solutions represents the cuckoo habitat as follows:

$$\text{Habitat} = [x_1, x_2, \dots, x_{N_{\text{var}}}], \quad (\text{A1})$$

where  $X$  is the vector of the solutions and  $N_{\text{var}}$  is the number of variables in the problem. A matrix of size  $N_{\text{pop}} \times N_{\text{var}}$  is generated.

Step 2. Evaluation.

The fitness of each line is evaluated, where  $N_{\text{pop}}$  is the number of lines. The habitat is evaluated as a fitness function.

Step 3. Egg allocation.

Dedicate some eggs to each cuckoo.

Step 4. Egg-laying radius.

The cuckoos start to lay eggs in the area according to a distance called egg-laying radius (ELR), as follows:

$$\text{ELR} = \alpha \times \frac{\text{Number of current cuckoo's eggs}}{\text{Total number of eggs}} \times (\text{var}_{\text{hi}} - \text{var}_{\text{low}}), \quad (\text{A2})$$

where  $\alpha$  is an integer and  $\text{var}_{\text{hi}}$  and  $\text{var}_{\text{low}}$  are the upper and lower bounds of the variables. Some eggs will be destroyed by the host birds and 10% of the survival cuckoos will starve.

Step 5. Migration.

When the cuckoos become mature, the cuckoos' swarm will migrate to achieve the best goal. The different groups are classified using the  $K$ -means clustering. Each cuckoo fly  $U\%$  of all the way toward destination (where  $U$  is a random number uniformly distributed between 0 and 1), with a deviation  $\varphi$  ( $\Pi/6$  rad).

Step 6. Population limit.

A maximum number of cuckoos is considered to limit the population.

Step 7. Repeat steps 2 to 6 until the stopping condition is satisfied.