

## Optimal replacement policy for obsolete components using cuckoo optimization algorithm based-approach: Dependability context

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*Received 29 May 2012; revised 24 August 2012; accepted; 30 October 2012*

In this paper, we present an optimization approach to deal with technological obsolescence in the case of several components. A component becomes obsolete when a challenger unit is available and possessing the same functionalities, but with more recent performances. The proposed approach includes the costs, failures rates, replacement teams, aging, energy consumption and the increasing technology rates. The budget constraint is formalized to select the components should be replaced and the model is based on cuckoo optimization algorithm (COA).

**Keywords:** Replacement policy, Obsolescence, Cuckoo optimization algorithm, Aging

### Introduction

Dependability activity is of fundamental importance for the safe and efficient operation of any industrial plant. In most papers which aim to study the dependability of industrial plant, the authors take into account the monitoring of the installations or the reliability of components.<sup>1-5</sup> The technological obsolescence of a component is characterized by the existence of a challenger unit possessing the same functionalities, but displaying higher performances. The obsolescence has an impact on the life-cycle of the component due to the unavailability of spare parts. On the other hand, it can be more and more difficult or costly to find old-generation component to replace degraded unit. At the same time, it is economically more interesting to replace the old-component gradually to benefit from their residual lifetime. The industrial enterprise seeks the optimal policy to deal with obsolescence. The aim of this paper is therefore to define an approach to deal with obsolescence at the engineering level in order to select the components considered optimal in the replacement policy.

### Literature review

Various authors have studied the technological obsolescence, but several efforts are necessary to address the problem in the context of dependability. Borgonovo *et al*<sup>6</sup> proposed a model in the case of one single component subject to obsolescence. The preventive maintenance of this component is undertaken at regular intervals and the repairs are considered. They consider that these maintenances and repairs maintain this component in the same initial state. The authors decided to model the probability of failure of this component by a constant failure as follows:

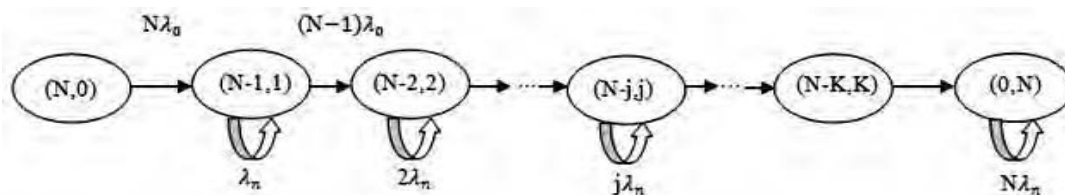
$$\lambda^* = \left(\frac{1}{\alpha}\right)^\beta T_{IM}^{\beta-1} \quad \dots(1)$$

where  $T_{IM}^{\beta-1}$  is the interval of maintenance,  $\alpha$  is the scale parameter (expressed in time units) and  $\beta$  is the shape parameter of a Weibull distribution. The authors propose that this component can be either periodically maintained or replaced by a technologically more advanced unit and the costs are assessed using Monte Carlo simulation.

Work of Elmakis *et al*<sup>7</sup> is characterized by this assumption: the failure rate  $\lambda_o$  of each component is constant. The proposed approach in this model is called

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Fig. 1—Diagram of the  $K$  strategy

“ $K$  strategy” (Fig. 1). The authors proposed a Monte Carlo simulation and evaluated the costs generated by each value of  $K$ . Mercier<sup>8</sup> proposed a model for  $N$  identical components with non-constant failure rates. These failure rates follow a Weibull law of the form. In the paper of Michel *et al*<sup>9</sup> the notion of “ $K$  strategy” has been extended by taking into account the failure rates as a Weibull law of the form. Dutt *et al*<sup>10</sup> discussed about the obsolete technology in the paper industries in India. Park *et al*<sup>11</sup> described the higher rate of the obsolescence and its impact vis-à-vis manufacturing sectors, but they not propose a strategy to deal with this phenomenon. Velavan *et al*<sup>12</sup> showed the importance of dealing with obsolescence in the textile industry and they consider in their work that the modern technologies consume less water and stream compared to obsolete technologies. Clavareau and Labeau<sup>13,14</sup> presented a model for  $N$  identical components using the  $K$  strategy and they develop a Monte Carlo methodology to evaluate the costs and to seek the value of  $K$ , but they not take into account the budget.

Min and Kim<sup>15</sup> presented the scheduling of the obsolescence study with the maintenance, but only on logistic assumptions. Karamouzian *et al*<sup>16</sup> studied the cost of the technological obsolescence and his impact in the industry. Romero Rojo *et al*<sup>17</sup> presented a state-of-the-art but only in the economic context. Sun *et al*<sup>18</sup> proved the influence of technological obsolescence on the product quality loss when the industrial plant contains obsolete components, but they have not proposed a solution. Kumar and Saranga<sup>19</sup> developed mathematical models to calculate the impact of various obsolescence mitigation strategies of an industrial system. They used the classical method of operational research to identify the best strategy for managing obsolescence. The disadvantages of this approach are that focuses only in the economic issue and it cannot take into account the failure rates and the aging. There are also others papers that aim to study the obsolescence and its impact on the industrial plants, but they do not take into account the parameters of the dependability<sup>20-25</sup>.

## Model description

### Problem Formulation

Previous works cited in Section 2 envisaged this problem in a simplified way. In this paper, we propose a more realistic approach and another way of the problem at the engineering level. This paper is characterized by the following assumptions: A set of  $N$  different components subject to technological obsolescence and challenger units are available. The enterprise decides to make the transition from the old to a new generation at the end of the year, according to the budget for technological obsolescence. The decision maker of the enterprise seeks to select the optimal components should be replaced and the remaining their residual lifetime will be exploited. The parameters related to each component are the following:

- Failure rate.
- Acquisition and implementation cost of the new-type component (challenger).
- Aging rate: the aging is important to be integrated into the model because it is an amount which influences the failure rate. This aging rate decreases the lifetime of the old-type component during the time. It was introduced by several authors as follows<sup>26</sup>

$$I(t) = I_0 + a \cdot t \quad \dots(2)$$

where  $I_0$  is a constant term,  $a$  is the aging rate and  $t$  is the time.

- Replacement team: number of different types of specialized replacement teams necessary for implementation of the new-type component.
- Lower energy consumption rate of the challenger compared with the old-type unit. This value represents that the new-type component consumes a lesser rate of energy compared with the old type unit.
- Increasing technology rate of the challenger compared with the old-type unit, such as e.g.,

measurement precision, memory capacity, response time, noiseless, ergonomy, etc.

The parameters of each component can be summarized as follows:

$$Comp_n \begin{cases} I_n \\ C_n \\ a_n \\ T_n \\ E_n \\ H_n \end{cases} \quad (n = 1, \dots, N) \quad \dots(3)$$

where  $Comp_n$  is the index of the component (for  $n = 1, \dots, N$ ),  $I_n$  is the failure rate of the old-type unit,  $C_n$  is the acquisition and implementation cost of the challenger,  $a_n$  is the aging rate of the old-type unit,  $T_n$  is the number of replacement team,  $E_n$  is the lower energy consumption rate and  $H_n$  is the increasing technology rate of the challenger.

It is to identify the optimal components that should be replaced by the new-type units (challengers), under these considerations like budget, optimal benefiting from the residual lifetime of the old-type units and at the same time facilitate the quickness transition from the old to the new generation to deal with obsolescence. To solve this, the fitness function is as follows:

*Maximize*

$$fitness = \sum_{n=1}^N \left( I_n + \frac{1}{C_n} + a_n + \frac{1}{T_n} + E_n + H_n \right) \quad \dots(4)$$

subject to

$$\sum_{n=1}^N C_n \leq budget \quad \dots(5)$$

The fitness function (4) seeks the maximum number of components which should be replaced, but under considering the budget (5). Furthermore, this fitness function seeks the components which have: higher failure and aging rate, saver energy consumption and increasing technology rate of the challenger, and at the same time the lesser cost of the challenger. To reach the fixed objectives and to respect the imposed conditions, the proposed solution consists of developing an approach

using an evolutionary algorithm. We opt to use an evolutionary algorithm because in this case we have meaningful data, not simple mathematical values. Each value represents a parameter and the evolutionary algorithm seeks the optimum among them.

**Cuckoo Optimization Algorithm (COA) Methodological Approach**

Optimization is the process of making something better and to find the maximum or the minimum of a fitness which expresses the optimization problem. There are a wide range of evolutionary optimization algorithms. Metaheuristic algorithms are often nature-inspired, and they are now among the most widely used algorithms for optimization<sup>27</sup>. The cuckoo optimization algorithm (COA) is one of several recent and powerful metaheuristics. The first evolutionary algorithm which is inspired by the cuckoos and their lifestyle was developed by Yang & Deb, called “Cuckoo Search”<sup>28-30</sup>. The cuckoo search algorithm proposed by Yang & Deb is based on the obligate brood parasitic behavior of some cuckoo species in combination with the Lévy flight behavior of some birds and fruit flies. A comparison study between the cuckoo search algorithm and other metaheuristics has been presented in several works<sup>31-33</sup>. Rajabioun<sup>34</sup> developed another algorithm based on cuckoo lifestyle, called “Cuckoo Optimization Algorithm (COA)”. He proved the efficiency of his algorithm via a benchmarking study. COA is the most suitable for discrete problems. Moreover, he proved the fast convergence and global optima achievement of his algorithm.

The basics of the algorithm developed by Rajabioun<sup>34</sup> have been used in this study. A random population of potential solutions (candidate components) is generated. These potential solutions represent the nests in COA. The parameters of the candidate components will be evaluated in the fitness function and a violation term is considered for the constraint. The steps to seek the optimum solution are given as follows. First, the algorithm starts with an initial population of cuckoos and they have some eggs to lay in some host bird’s nests. Some of these eggs which are more similar to the host bird’s eggs have the opportunity to grow up and become a mature cuckoo. Other eggs are detected by host birds and are destroyed. The hatched eggs reveal the suitability of the nests in that area. The more eggs that survive and hatch in the area, the more profit is gained in that area. So the position in which more eggs survive will be the term that COA is going to optimize. Each cuckoo has a “*cuckoo’s distance*” to the goal point (best habitat).

In order to solve a problem using COA, it is necessary that the values of the problem be formed as an array, called "habitat". In the case of  $N_{var}$  dimensional problem, a habitat is an array of  $1 \times N_{var}$ , representing the current living position of the cuckoo. It is defined as follows:

$$habitat = [x_1, x_2, \dots, x_{N_{var}}] \quad \dots(6)$$

The profit of a habitat is obtained by evaluation of profit function  $f_b$  at a habitat of  $(x_1, x_2, \dots, x_{N_{var}})$ , where:

$$profit = f_b(habitat) = f_b(x_1, x_2, \dots, x_{N_{var}}) \quad \dots(7)$$

To start the optimization algorithm, a candidate habitat matrix of size  $N_{pop} \times N_{var}$  is generated. Some randomly produced number of eggs is postulated for each of these initial cuckoo habitats. Another point is that the cuckoos lay eggs within a maximum distance from their habitat, this range is called "Egg Laying Radius (ELR)". This ELR is given as follows:

$$ELR = a \times \frac{\text{Number of current cuckoo's eggs}}{\text{Total number of eggs}} \times (var_{hi} - var_{low}) \quad \dots(8)$$

where  $a$  is an integer supposed to handle the maximum value of ELR,  $var_{hi}$  and  $var_{low}$  are respectively the upper limit and the lower limit for variables. After the egg laying process,  $p\%$  of all eggs (usually 10%), with lesser profit values, will be destroyed. These eggs have no chance to hatch. The rest of the eggs incubate in hosts' nests, hatch and the hatchlings are fed by host birds. Another point is that the cuckoo groups are formed in different areas and to immigrate to the best society it is difficult to recognize which cuckoo belongs to which group. The author of the algorithm proposes to done with  $K$ -means clustering method. When moving toward goal point, the cuckoos do not fly all the way to the destination habitat. They fly only part of the way and also have a deviation. However, each cuckoo flies only  $I\%$  of the total distance toward goal habitat and also has a deviation of  $f$  radians. These two parameters,  $I$  and  $f$ , help cuckoos search many more positions in all environments. For each cuckoo,  $I$  and  $f$  are defined as follows:

$$\begin{aligned} I &\sim U(0, 1), \\ j &\sim U(-w, w) \end{aligned} \quad \dots(9)$$

where  $I \sim U(0,1)$  means that  $I$  is a random number (uniformly distributed) between 0 and 1.  $w$  is a parameter that constraints the deviation from goal habitat. The author recommends an  $w$  of  $\pi/6$  (radian) seems to be enough for good convergence.

The cuckoo optimization algorithm (COA) is summarized as follows<sup>34</sup>:

- Initialize cuckoo habitats with some random points on the profit function;
- Dedicate some eggs to each cuckoo;
- Define ELR for each cuckoo;
- Let cuckoo to lay eggs inside their corresponding ELR;
- Destroy those eggs that are recognized by host birds;
- Let eggs hatch and chicks grow;
- Evaluate the habitat of each newly grown cuckoo;
- Limit cuckoos' maximum number in environment and kill those who live in worst habitats;
- Cluster cuckoos and find best group and select goal habitat;
- Let new cuckoo population immigrate toward goal habitat;
- If stop condition is satisfied, then stop. If not, go to 2.

### Case study: manufacturing plant

It is considered that a set of  $N = 50$  different component units, likely to be replaced by their more performing challengers. These units are subject to failures and aging. The new-type units will perform better according to two criteria: their lower energy consumption and increasing technology rates relative to those of the old ones. The enterprise decides to make the transition from an old to a new generation of the components units. The special budget to deal with obsolescence is:  $budget = 40 \cdot 10^3 \$$ . The objective function is given by (10) and the data of these components are reported in Table 1.

Maximize

$$fitness = \sum_{n=1}^{50} \left( I_n + \frac{1}{C_n} + a_n + \frac{1}{T_n} + E_n + H_n \right) \quad \dots(10)$$

subject to

Table 1—Numerical value of the data

$Comp_n$	$I_n \times 10^{-3} (y^{-1})$	$C_n \times 10^3 \$$	$a_n \times 10^{-3}$	$T_n$	$E_n$	$H_n$
1	2.16	0.82	3.45	1	0.0850	0.25
2	3.80	1.03	1.07	1	0.0923	0.18
3	1.77	0.95	2.30	3	0.1110	0.32
4	2.34	1.44	3.96	2	0.0721	0.29
5	2.17	2.12	2.37	1	0.0620	0.31
6	3.26	1.71	4.61	2	0.0743	0.45
7	4.05	0.86	1.56	2	0.1010	0.19
8	5.63	1.81	3.83	1	0.0912	0.20
9	3.44	2.95	5.95	3	0.0837	0.34
10	4.07	3.84	1.07	1	0.0594	0.47
11	5.01	2.71	1.88	1	0.0631	0.38
12	4.29	3.62	6.56	3	0.0571	0.22
13	6.40	1.93	3.19	1	0.0681	0.15
14	4.85	0.80	7.22	2	0.0488	0.21
15	3.28	2.94	3.59	1	0.0520	0.11
16	7.18	3.20	3.09	2	0.0912	0.10
17	1.92	1.15	2.16	1	0.1000	0.27
18	2.61	2.75	7.14	1	0.0955	0.33
19	5.74	3.08	1.67	3	0.0273	0.24
20	6.03	1.47	2.13	2	0.0135	0.31
21	2.98	0.81	2.41	2	0.0391	0.23
22	7.67	1.10	3.78	1	0.0566	0.31
23	3.09	2.03	1.25	2	0.0483	0.40
24	5.22	1.90	6.01	1	0.0961	0.13
25	4.71	2.35	3.16	1	0.1052	0.25
26	6.35	3.41	1.44	1	0.0837	0.31
27	2.59	1.26	5.76	3	0.0294	0.42
28	5.82	3.73	1.68	1	0.0478	0.30
29	1.49	0.97	4.71	2	0.0741	0.48
30	4.63	2.93	3.91	1	0.0269	0.18
31	1.83	1.62	1.46	2	0.0783	0.23
32	7.20	3.52	3.90	1	0.0175	0.14
33	5.91	2.45	3.60	1	0.0121	0.26
34	2.50	1.08	7.71	1	0.0258	0.49
35	4.08	0.80	3.66	2	0.0425	0.36
36	3.71	0.91	1.22	1	0.0093	0.46
37	7.17	2.85	2.61	2	0.0500	0.39
38	1.45	2.01	3.82	1	0.0705	0.40
39	3.18	3.61	1.97	1	0.0433	0.50
40	5.03	0.92	3.08	3	0.1260	0.38
41	7.82	1.76	2.59	2	0.0500	0.30
42	2.93	3.51	2.17	1	0.0800	0.42
43	6.34	1.82	1.48	1	0.0107	0.45
44	4.21	2.44	2.34	2	0.0095	0.51
45	7.13	3.08	5.02	2	0.0210	0.40
46	2.63	0.90	3.16	1	0.0103	0.49
47	6.71	1.47	4.70	1	0.0104	0.32
48	4.33	3.68	2.33	2	0.0572	0.50
49	7.55	2.55	7.84	1	0.0335	0.44
50	1.69	0.83	1.51	2	0.1140	0.39

Table 2—COA parameters

COA property	Value
Dimension of the problem to optimize (number of components)	50
Number of initial population of cuckoos	10
Minimum number of eggs for each cuckoo	2
Maximum number of eggs for each cuckoo	4
Maximum iterations of the cuckoo algorithm	20
Maximum number of cuckoos that can live at the same time	200
Radius coefficient (control parameter of egg laying)	50

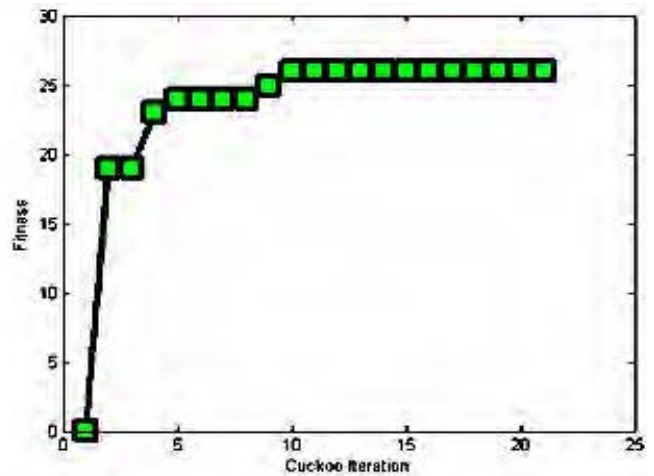


Fig. 2— Result of the COA process for the optimal replacement policy

$$\sum_{n=1}^{50} C_n \leq 40 \cdot 10^3 \quad \dots(11)$$

The components followed a Weibull law of the form which is given by (12).

$$I(t) = \frac{b}{m} \left( \frac{t-g}{m} \right)^{b-1} \quad \dots(12)$$

where  $\mu$  is the scale factor,  $\beta$  is the shape factor,  $g$  is the location parameter and  $t$  is the time. Table 2 contains the parameters of the COA implemented in order to solve our problem. The values of the parameters were chosen based on trial-and-error tuning, to achieve proper convergence.

The result in Fig. 2 shows that as the number of iterations increases beyond five, the fitness increases rapidly and then converges to an appropriately high value.

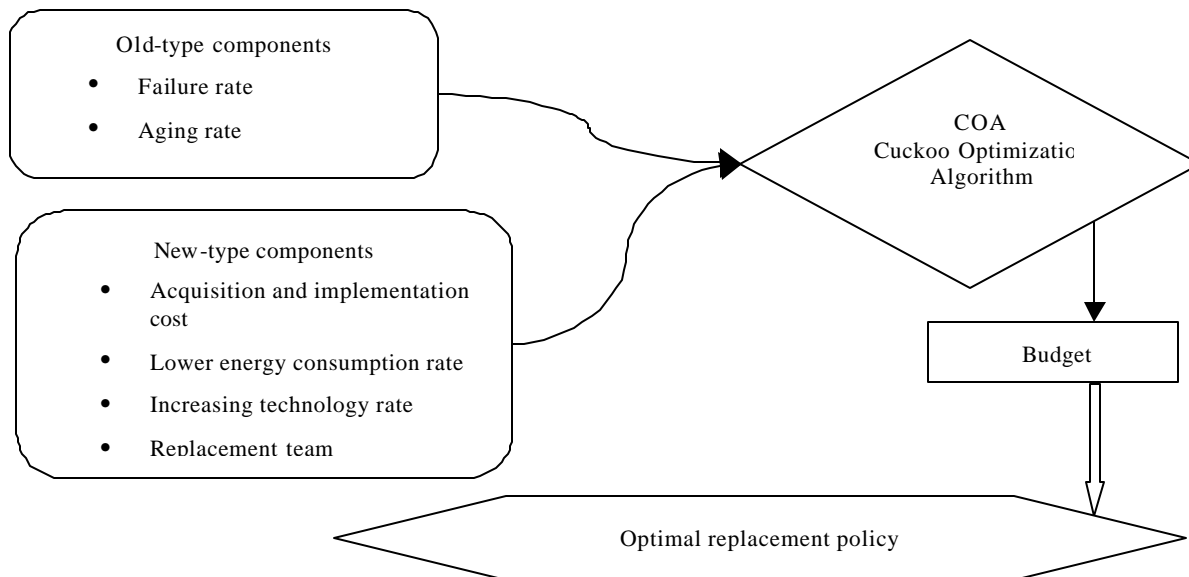


Fig. 3—Proposed model in this paper

Table 3—Components should be replaced by the new-type units

1	15	27	43
2	17	29	44
3	19	33	46
6	20	35	47
8	21	36	50
11	23	38	
14	24	40	

The algorithm has been run for different times. The characteristic of the COA for fast convergence allowed us to obtain the results at a low number of iterations (10 iterations). Table 3 contains the optimal components to be replaced. The number of components which should be replaced is 26, whereas for the remaining their residual lifetime will be exploited. On the other hand, we can notice that more than half the number of old-type components will be replaced by the new-type units and the residual from the budget is 90\$.

**Conclusions**

The goal of this paper was to propose a new approach to deal with technological obsolescence of industrial plants. A case study is presented to illustrate our approach. The proposed model is in another and a more realistic way compared with previous works available in the literature. The methodology is

characterized by the parameters of the dependability. This model can be applied to several industrial plants, such as e.g., production lines, power plant, communication station, etc. On the other hand, this approach makes the rapid transition, according to the budget and the considered parameters. The optimization is based on an evolutionary algorithm using cuckoo optimization algorithm (COA). The advantages of COA facilitate this type of replacement which helps the enterprise to make the optimal transition policy via the selection of an optimum. Fig. 3 illustrates the general organization chart of our proposed model to deal with obsolescence.

**Acknowledgements**

The authors thank the editor and referees for their valuable comments and suggestions, which considerably improved the presentation of this article.

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