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Optimal Selection of Obsolete Tools in Manufacturing Systems Using Cuckoo Optimization Algorithm

Mohamed Arezki Mellal*[a], Smail Adjerid[a], Edward J. Williams[b,c]

[a]LMSS, Faculty of Engineering Sciences (FSI), M'Hamed Bougara University, Boumerdès, Algeria
[b]Decision Sciences, College of Business, University of Michigan, Dearborn, Michigan, USA
[c]Industrial and Manufacturing Systems Engineering Department, College of Engineering and computer Science, University of Michigan, Dearborn, Michigan, USA
mellal.mohamed@gmail.com

Technological obsolescence has an impact on the lifecycle of tools in manufacturing systems. In our work, a model dealing with the replacement of obsolete items based on a modern evolutionary algorithm, called Cuckoo Optimization Algorithm is applied to degrading tools in manufacturing systems. The proposed method can select the optimal tools which should be replaced by the new-type ones in the context of dependability. A case study is presented to illustrate the methodology.

1. Introduction and background

Most published works dealing with the maintenance of tools in manufacturing plants are focused on the downtime or the performance loss of each tool. On the other hand, the authors consider that these tools are replaced by identical units. Nowadays, the reality is quite different and new-generation units are available. Technological obsolescence of a tool is characterized by the existence of a new-type unit displaying the same functionalities, but with higher performances (such as: improved material, higher finishing level, etc.).

In the literature, we can find several approaches devoted to the replacement of industrial assets subject to technological obsolescence.

Borgonovo et al. (2000) studied the case of one-single obsolete asset. They concluded that this asset can be replaced by a more performed unit or maintained at a fixed period. Several works were based on a so called "*K* strategy" e.g. (Elmakis et al., 2002; Michel et al., 2004; Mercier, 2008; Clavareau and Labeau, 2009). The main basis of this kind of strategy were given as follows: first, new-type assets are used only to replace failed old-type units; then, after *K* corrective actions of this kind, the $N-K$ old-type remaining assets are preventively replaced by new-type ones at the time of the K^{th} corrective intervention. The "0" strategy represents the preventive replacement of all old-type assets at the initial moment. Mellal et al., 2012; Mellal et al., 2013a; Mellal et al., 2013b) proposed new approaches based on a modern bio-inspired algorithm called Cuckoo Optimization Algorithm (COA) and Genetic Algorithms (GA). These approaches are characterized by a flexible model and the algorithms can select the optimal assets which should be replaced, by considering several parameters and the budget as a constraint. However, the replacement strategy of obsolete tools in manufacturing systems has not been investigated in an efficient study. Sun and Xi (2011) proposed maintenances policies for degrading tools by considering the technological obsolescence, but as a coefficient in the model.

In this work, we applied the flexible model (Mellal et al., 2012) for the replacement of obsolete tools in a manufacturing plant. Some parameters are considered to select the optimum among them:

$$\underset{\varsigma\in N}{\text{Maximize}\ \psi}\ :\sum_{i=1}^{N}\left(Function\, of\ the\ parameters\right) \tag{1}$$

where *N* is the total number of obsolete components in the plant and ς is the optimum.

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s.t

$$\text{Total cost} \leq Budget \tag{2}$$

The remainder of the paper is organized as follows: Section 2 describes the basis of COA; Section 3 presents a case study, the formulated problem and the results using COA. Finally, some conclusions are drawn in Section 4.

2. Cuckoo optimization algorithm (COA)

Nowadays, bio-inspired algorithms are widely used in engineering, such as: genetic algorithms for hybrid distillation processes (Bravo-Bravo et al., 2011) and particle swarm optimization for tile manufacturing processes (Navalertporn and Afzulpurkar, 2011).

Cuckoo optimization algorithm (COA) is one of the latest, powerful and prevailing bio-inspired algorithms, developed in 2009 by Ramin Rajabioun (Rajabioun, 2011). This algorithm is inspired by the life of a bird family, called *Cuckoo*.

The cuckoos belong to the “brood parasites family”, birds which lay eggs in the nest of another species. These cuckoos parasitize the nests of a large variety of bird species and carefully mimic the color and pattern of their own eggs. How the cuckoos manage to lay eggs is the fundament of COA.

Each cuckoo starts laying eggs randomly in some other host birds’ nests within a given area called “habitat”:

$$\text{Habitat} = \left[x_1, x_2, \ldots, x_n, \ldots, x_N\right] \tag{3}$$

where x_n represents the index of the nest (obsolete industrial item).

Furthermore, each cuckoo lays eggs within a distance called “Egg Laying Radius, ELR”:

$$ELR = \alpha \times \frac{Number\ of\ current\ cuckoo's\ eggs}{Total\ number\ of\ eggs} \times \left(var_{hi} - var_{low}\right) \tag{4}$$

where α is an integer supposed to handle the maximum value of ELR, var_{hi} and var_{low} are the upper limit and the lower limit for variables, respectively.

After all cuckoos’ eggs were laid in the obsolete industrial items (host nests), some of them are randomly destroyed (as they are less similar to the host birds’ own eggs). At this step, the items whose all the cuckoos’ eggs were destroyed, they are removed from the habitat. The profit of a habitat is to maximize the number of survival hatched eggs (number of replaced tools).

The undestroyed eggs will hatch and grow in the host nests. After a given period, the mature cuckoos will migrate to the best habitat. The groups of cuckoos are recognized using *K*-means clustering.

However, the cuckoos only fly λ% of the way with a deviation amount φ (radians):

$$\lambda \sim U(0,1),\ \varphi \sim U(-\omega, \omega) \tag{5}$$

where λ is a random number uniformly distributed between 0 and 1. ω is a deviation parameter. The author of COA advises: $\omega=(\pi/6)$ rad.

The basic algorithm of COA is given by the follows steps (Rajabioun, 2011):

- Initialize the habitats with some random points on the profit function;
- Dedicate some eggs to each cuckoo;
- Define ELR for each cuckoo;
- Let cuckoos to lay eggs inside their corresponding ELR;
- Destroy those eggs that are recognized by host birds;
- Let eggs hatch and chicks grown;
- Evaluate the habitat of each newly grown cuckoo;
- Limit cuckoos’ maximum number in environment and kill those who live in worst habitats;
- Cluster cuckoos, find best group and select goal habitat;
- Let new cuckoo population migrate toward goal habitat;
- If stop condition is satisfied, stop; otherwise, go to 2.

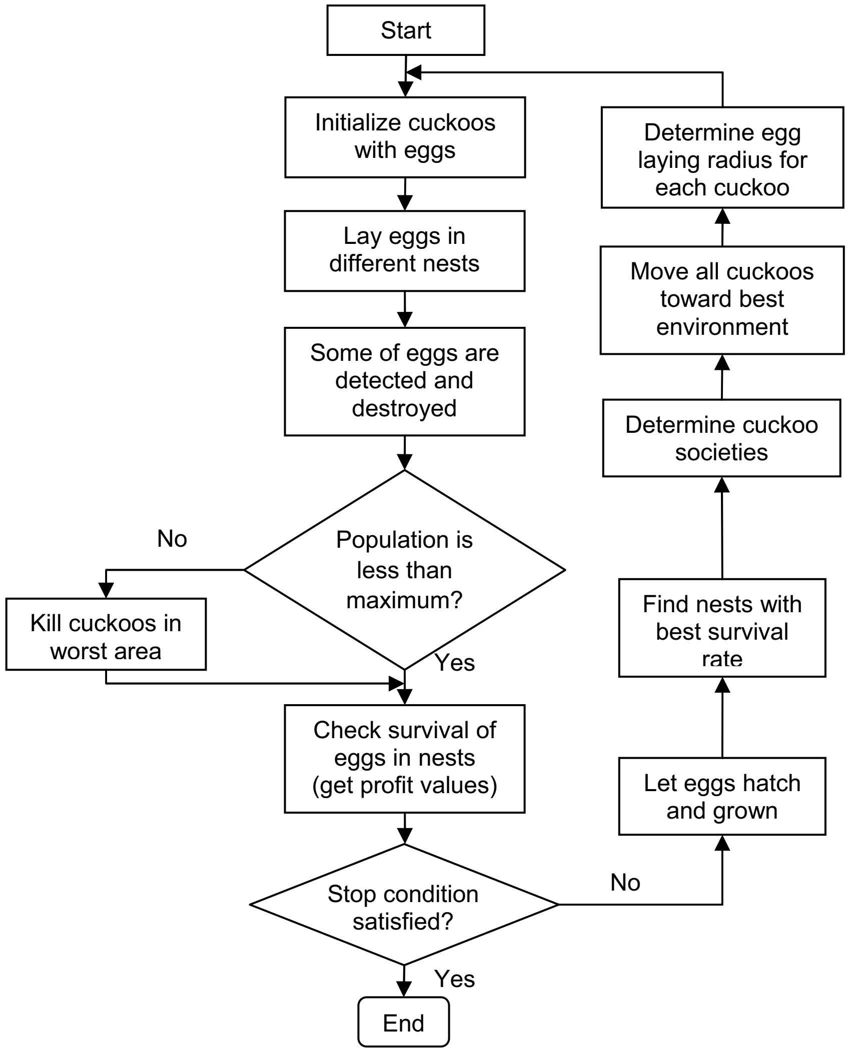

Figure 1: Flowchart of COA (Rajabioun 2011).

Figure 1 shows the general flowchart of COA. This bio-inspired metaheuristic displays several advantages, such as: proper convergence, rapid convergence after a few iterations and the global optimum is globally guaranteed.

3. Case study

In this paper, the case of a manufacturing plant consisting of two stations is studied. Table 1 reports the operations and the number of obsolete tools in each station.

Table 1: Plant information

Station	Operations	Number of obsolete tools (*N*)	Budget ($)
1	Milling	10	620
2	Drilling/Boring hole	12	1000

To select the optimal tools, we consider the following parameters:

- Old-generation unit: failure rate (λ_i), mean degradation drift rate(μ_i), quality loss coefficient (Q_i).
- New-generation unit: purchase and implementation cost (C_i), increasing technology rate which represents an improvement in the materials (ξ_i).

The values of various parameters related to each tool are listed in Tables 2 and 3 for the stations 1 and 2, respectively.

Table 2: Data of the station 1

$Tool_{1,i}$	$\lambda_{1,i} \times 10^{-5}$	$\mu_{1,i}$ (mm/h) $\times 10^{-5}$	$Q_{1,i}$ (\$/mm²)	$C_{1,i}$ (\$)	$\xi_{1,i}$
1	2.00	3.115	1.01	120	0.45
2	5.10	2.456	0.98	95	0.37
3	3.70	3.012	1.27	97	0.30
4	4.26	1.658	2.03	102	0.29
5	2.10	3.478	1.66	110	0.37
6	3.50	2.009	2.04	94	0.28
7	4.25	1.958	0.99	90	0.21
8	2.00	3.659	1.79	115	0.44
9	5.17	2.784	2.07	105	0.38
10	3.80	2.109	1.41	100	0.44

Table 3: Data of the station 2

$Tool_{2,i}$	$\lambda_{2,i} \times 10^{-5}$	$\mu_{2,i}$ (mm/h) $\times 10^{-5}$	$Q_{2,i}$ (\$/mm²)	$C_{2,i}$ (\$)	$\xi_{2,i}$
1	3.10	1.784	2.35	150	0.51
2	4.07	3.782	1.77	120	0.49
3	3.89	2.036	2.08	117	0.55
4	2.78	1.987	1.90	165	0.38
5	4.12	2.478	2.50	136	0.51
6	2.72	3.421	2.41	117	0.62
7	3.64	1.847	1.85	145	0.39
8	2.09	2.369	2.63	120	0.46
9	4.21	2.897	1.72	160	0.65
10	3.88	3.418	2.65	157	0.50
11	2.93	1.985	1.98	138	0.62
12	2.75	2.968	1.85	124	0.48

According to the model (Mellal et al., 2012), the present problem can be formalized as follows:
Station 1:

$$\text{Maximize}\,\psi_1 : \sum_{i=1}^{N}\left(\lambda_{1,i} + \mu_{1,i} + Q_{1,i} + \frac{1}{C_{1,i}} + \xi_{1,i}\right) \tag{6}$$

s.t:

$$\sum_{i=1}^{N} C_{1,i} \leq Budget_1 \tag{7}$$

Station 2:

$$\text{Maximize}\,\psi_2 : \sum_{i=1}^{N}\left(\lambda_{2,i} + \mu_{2,i} + Q_{2,i} + \frac{1}{C_{2,i}} + \xi_{2,i}\right) \tag{8}$$

s.t:

$$\sum_{i=1}^{N} C_{2,i} \leq Budget_2 \tag{9}$$

Table 4 presents the simulation parameters. The results of the implemented COA are shown in Figures 2 and 3, for the stations 1 and 2, respectively.

Table 4: COA rules and parameters

COA property	Value
Habitat size (number of obsolete tools)	10, 12
Number of initial cuckoos	10
Minimum number of eggs for each initial cuckoo	2
Maximum number of eggs for each initial cuckoo	4
Maximum number of cuckoos that can at the same time	200
Maximum iterations of the algorithm	20

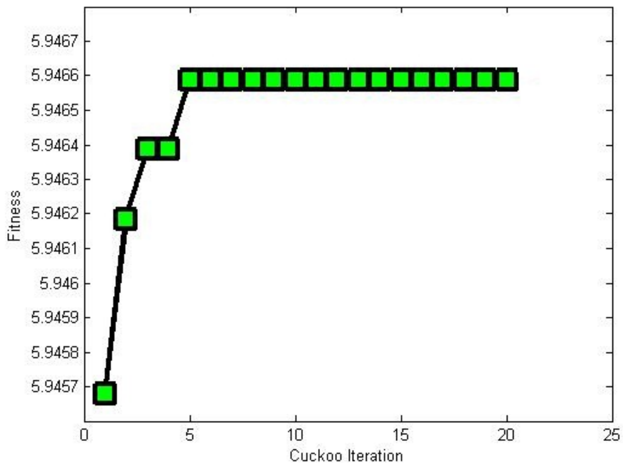

Figure 2: Results of COA process for the optimal tools in the station 1.

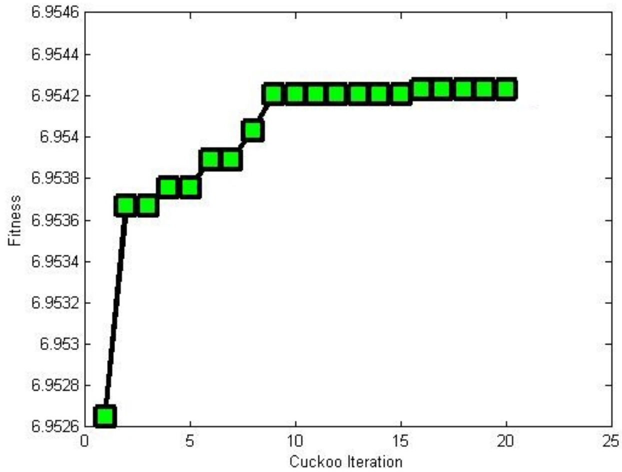

Figure 3: Results of COA process for the optimal tools in the station 2.

The algorithms have been run for different times and the stop criterion was fixed at 20 iterations. The selected obsolete tools are reported in Table 5. These tools are replaced by the new-type units, while the remaining old-generation tools are maintained according to the regular maintenance schedule.

Table 5: Selected obsolete tools

Station 1	Station 2
1, 2, 5, 7, 9, 10	2, 4, 5, 6, 7, 9, 10

4. Conclusions

The present work presented a replacement approach for obsolete tools in a manufacturing plant by applying a modern model. To select the optimum, five parameters were considered in the formulated problem. The advantage of COA for proper convergences provides realistic results at lower iterations. Furthermore, the global optimum can be reached easily.

Other possible future works include an application of this approach to different types of stations with several obsolete tools and compare the results with other evolutionary optimization techniques.

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