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Obsolescence optimization of electronic and mechatronic components by considering dependability and energy consumption

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Abstract: Nowadays, rapid technological progress influences the dependability of equipments and also causes rapid obsolescence. The mechatronic and electronic equipment components are mostly affected by obsolescence. A new challenger unit possesses identical functionalities, but with higher performances. This work aims to find the optimal number of components which should be replaced by new-type units, under budgetary constraints. In this work, the new challenger unit is characterized by lower energy consumption and the optimization steps are based on genetic algorithm (GA). The result shows the importance of this type of replacement in order to economize energy consumption and to deal with obsolescence.

Key words: obsolescence; lower energy consumption; mechatronic and electronic components; genetic algorithm

1 Introduction

Often, the study of dependability of mechatronic and electronic components is based only on monitoring, diagnosis and failures, but the obsolescence is not considered in the model (e.g., Refs. [1−4]). The technological progress has an impact on the life-cycle of components due to the unavailability of spare parts, therefore, if this phenomenon is ignored, implicitly the dependability of these components decreases.

New components are available to achieve the same missions, but with higher performances. These higher performances can be understood as smaller failure rates and lower energy consumption. At the same time, it is difficult to optimally schedule the replacement of old component units by new-type units. However, it is economically more promising to replace the old-type units gradually to benefit from their residual lifetime. The aim of this work is therefore to define the optimal number of obsolete components to be replaced by new challenger units. In this work, the new challenger is characterized by lower energy consumption and the main idea of our model is based on optimization steps using genetic algorithm (GA) rules.

2 Overview of obsolescence

The various manifestations of obsolescence have been studied by multiple academic disciplines. For example, in economics, obsolescence is an important problem discussed in the context of durability [5]. In the sciences of engineers, obsolescence is a phenomenon that decreases the dependability of equipment components. In the literature, we can find several articles which aim at the optimization of replacement under technological progress (obsolescence).
ELTON and GRUBER [5] were the first to study obsolescence. They considered only one component characterized by an annual revenue, a purchase cost, a resale value which decreases with the age of this component and an aging factor which reduces the revenue. They considered that technological progress is reflected in continuous and linear increase of the efficiency, and this efficiency is given in the model by an increase of annual revenue of the new component with g factor. Their proposed model does not provide description of the failure modes of components, but takes into consideration their age by a linear decrease of the revenue generated over time of the new component with

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h factor. The proposed model in Ref. [5] is given as follows:

$$rT+\mathrm{e}^{-rT}=1+\frac{r^2(I-S)}{(g+h)-rs} \tag{1}$$

where r is the discount rate for a period t; I is the purchase cost of the old component; S is the purchase cost of the new component; s is the resale value per time unit of the operating and T is the time interval for component replacement. The authors of this work proposed that the strategy which maximizes the income consists of replacing the component at time interval T, where T is the solution of Eq. (1).

SCHOCHETMAN and SMITH [6] considered one component subject to obsolescence and the replacement strategy is at time of the appearance of the new challenger and they neglect the failure rates of the old component.

HRITONENKO and YATSENKO [7] considered a geometric technological change of several components and they searched for the optimum of Eq. (3).

$$L(t)=\int_{d(t)}^{t} m(\tau)\,\mathrm{d}\tau \tag{2}$$

$$\min I=\int_0^T \mathrm{e}^{-rt}\left(\int_{d(t)}^{t} q(\tau,t)m(\tau)\,\mathrm{d}\tau+p(t)m(t)\right)\mathrm{d}t \tag{3}$$

where $L(t)$ is the number of components, $d(t)$ is the installation time of obsolete components replaced in t, $m(t)$ is the number of new components implemented per time unit at the moment t, $q(\tau,t)$ is the operating cost at the moment t of one component implemented at t, $p(t)$ is the purchase and implementation cost of the new component at the moment t and r is the discount rate (>0). The constraint applicable to Eq. (3) is given as follows:

$$0\le m(t)\le M(t),\ d(t)\le t \tag{4}$$

where $M(t)$ is the number of old components. The authors of this work also neglected the failure rates.

In Refs. [5−7], the authors studied the problem of obsolescence only from the economic point of view. Several efforts are necessary to address the problem of obsolescence at the engineering level. We mention that some researches are available which aim to propose a more realistic approach [8−11]. These works introduced other parameters of engineering in their models.

In Ref. [8], the case of one single component subjected to aging was proposed in the model. 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:

$$\lambda^*=\left(\frac{1}{\alpha}\right)^{\beta} T_{\mathrm{IM}}^{\beta-1} \tag{5}$$

where $T_{\mathrm{IM}}^{\beta-1}$ is the interval of maintenance, α is the scale parameter (expressed in time units) and β is the shape parameter of the Weibull law of the form. The authors proposed that this component can be either periodically maintained or replaced by a technologically more advanced unit. The costs are evaluated using Monte Carlo simulation. This work cannot solve the problem of obsolescence in the case of several components.

In Refs. [12−13], the authors studied the following case: A set of N identical and independent components. These components can be either preventively or correctively replaced by new-type units, the replacements take a negligible time and the new-type units have higher performances [13].

The work of ELMAKIS et al [12] is characterized by the assumption that the failure rate λ_0 of each component is constant. The proposed approach in their model is called "K strategy" (Fig. 1) and it is based on the following: First, new-type components are used only to replace failed old-type units; Then, after K corrective actions of this kind, the $N-K$ old-type remaining components 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 components at the initial moment. To determine the value of K, the authors propose a Monte Carlo simulation to evaluate the costs generated by each value of K.

MERCIER [10] proposed a model for N identical components with non-constant failure rates. These failure rates follow a Weibull distribution. In the work of MICHEL et al [9], the notion of "K strategy" has been extended by taking into account the failure rates as a Weibull law of the form.

CLAVAREAU and LABEAU [11] proposed a model for N identical components, but with several

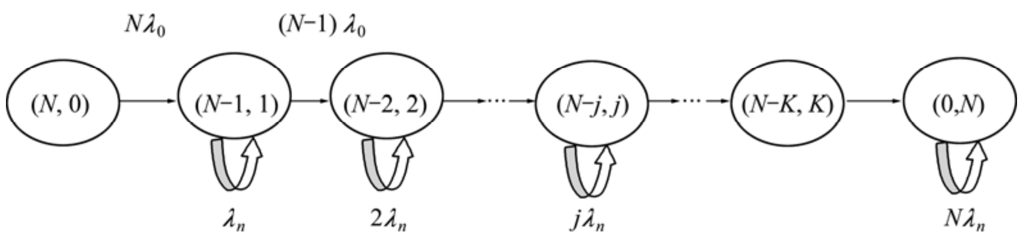

Fig. 1 Diagram of K strategy

challengers. A non-zero probability of incompatibility is accounted for, in order to model the fact that the on-site implementation of new-type components could turn out to be problematic, and some replacements might not be immediately successful, as technicians are perhaps yet unfamiliar with this new technology.

Later, DUBOS and SALEH [14] proved the importance of obsolescence problem optimization in the context of dependability by studying the risk of spacecraft on-orbit obsolescence. They developed a stochastic approach for quantifying and analyzing this risk. Markov models have been used to model the problem and a Monte Carlo simulation was established to evaluate the costs.

Previous works envisaged the study of obsolescence in a simplified way. In this work, another method of case study is presented.

3 Model description

In this work, we introduce a more realistic approach. We will consider a set of N components, likely to be replaced by their more performing challengers characterized by lower energy consumption rate. The enterprise decides to make the transition from the old to the new generation of components at the end of the year.

3.1 Parameters

The first step is to define the parameters. In order to model a realistic problem, the following parameters are considered:

1) Failure rates of the old-type components;

2) Purchase and implementation costs of the new-type components (challengers);

3) Lower energy consumption rate of the new-type unit. For example, BILIM [15] proposed energy saving in industrial machining via optimum cutting speed. However, the energy savings can be understood in the context of replacement of obsolete components.

Each component is represented by its parameters as follows:

$$I_{\mathrm{Comp},n}\begin{cases}\lambda_n\\ \eta_n\\ C_n\end{cases} \tag{6}$$

where $I_{\mathrm{Comp},n}$ is the index of the component (for n=1, $\cdots$, N), λ_n is the failure rate of the old-type unit, η_n is the lower energy consumption rate, and C_n is the purchase and implementation cost of the challenger.

The aim of our work is to identify the optimal components to be replaced by the new-type units (challengers), but under these considerations: budget, optimal benefiting from the residual lifetime of the old-type units and maximize the energy saving.

3.2 Optimization steps

To optimize our replacement, we use the rules of genetic algorithms (GAs). GAs are powerful optimization tool used in many research fields: job shop scheduling problem [16], minimizing the wear rate in gear pump [17], etc. GA was developed after the pioneering work of Holland [18]. In its general form, GA works through the following steps [19]:

1) Creation of a random initial population of potential solutions to the problem and evaluation of these individuals in terms of their fitnesses, i.e. of their corresponding objective function values;

2) Selection of a pair of individuals as parents;

3) Crossover of the parents, with generation of two children;

4) Replacement in the population, so as to maintain the population number constant;

5) Genetic mutation;

6) Repeat steps until satisfying solution is obtained.

The objective function (fitness) of our problem can be written as:

$$\mathrm{Max}\,Z=\sum_{n=1}^{N}\left(\lambda_n+\eta_n+\frac{1}{C_n}\right) \tag{7}$$

Subject to

$$\sum_{n=1}^{N}C_n\le B \tag{8}$$

where B is the budget.

The objective function (Eq. (7)) allows indentification of the optimal components (high failure rates, the most economical challenger, lesser purchase and implementation cost) to be replaced by the new-type of each one, but depending on the budget (Eq. (8)).

We use the following binary encoding:

1) Each gene (x_i^n) represents one component, and the number of genes per individual is equal to the number of components in order of appearance;

2) A random initial population of potential solutions is given;

3) $$(x_i^n)\begin{cases}1, & \text{if the component is marked in the individual}\\ 0, & \text{otherwise}\end{cases} \tag{9}$$

4) For all components assigned the value “1”, their parameters will be evaluated in the fitness. The genetic algorithm seeks the optimal solution through the generations until convergence.

5) Every time a new solution is proposed by the GA, the objective function is evaluated and a ranking of the individuals in the current population is dynamically updated, based on their fitness values. This ranking is used in the selection procedure.

3.3 Case study

A set of (N=14) components were used for case study. The study starts at the end of the year, the budget will be available (B=48×10^3\$) and we select the best challenger of each old-type component.

Table 1 contains the numerical value of the data. The failure rates of the components followed a Weibull law of the form and the function expression is shown as

$$\lambda(t)=\frac{\beta}{\mu}\left(\frac{t-\gamma}{\mu}\right)^{\beta-1} \tag{10}$$

where μ is the scale factor, β is the shape factor, γ is the location parameter and t is the time unit. As an example, for the challenger of the component-4 (Table 1), its lower energy consumption rate is 0.11, which means that this new-type component (challenger) has a rate of 0.11 lesser energy consumption compared with the old-type.

Table 1 Numerical value of the components

$I_{\mathrm{Comp},n}$	Failure rate λ_n/ $10^{-3}\mathrm{a}^{-1}$	Purchase and implementation cost of challenger C_n (10^3\$)	Lower energy consumption rate η_n
1	3.2	4.1	0.10
2	4.5	2.6	0.09
3	2.2	5.3	0.08
4	1.7	3.8	0.11
5	5.4	2.7	0.08
6	3.4	4.4	0.07
7	1.9	5.3	0.13
8	2.8	5.7	0.04
9	5.5	2.9	0.08
10	4.3	3.6	0.10
11	5.1	4.3	0.07
12	1.7	6.1	0.06
13	2.4	5.9	0.08
14	3.8	4.8	0.10

Table 2 contains the rules and the parameters for the GA implemented in order to solve the optimization problem.

Table 2 Parameters of implemented GA

GA property	Value
Number of genes for individual	14
Number of individuals (population size)	60
Number of generations (termination criterion)	350
Mutation probability	0.001
Selection technique	Standard roulette

3.4 Results and discussion

The results of the GA optimization process are shown in Fig. 2. It can be seen how, via the GA, its fitness converges. Each point represents a possible solution, and during the iterations, the algorithm converges to an optimal solution.

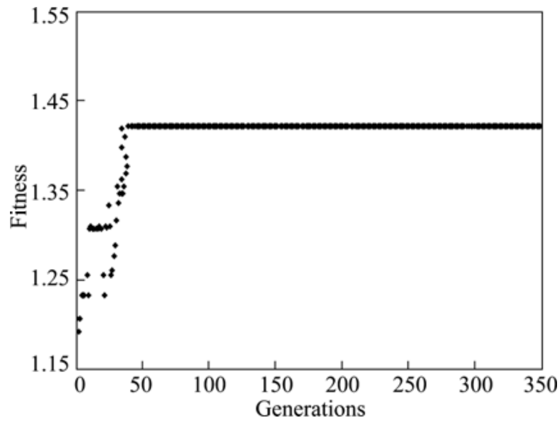

Fig. 2 GA process for optimal components to be replaced

We can see also that the convergence of the algorithm is at 45 iterations (generations). It was able to control the number of components with their parameters. Figure 3 shows the solution identified by our algorithm.

1	1	1	1	1	1	1	0	1	1	1	0	0	1

Fig. 3 Solution given by our algorithm

All components assigned "1" will be replaced by new-type units, whereas for $I_{\mathrm{Comp},8}$, $I_{\mathrm{Comp},12}$ and $I_{\mathrm{Comp},13}$, their residual lifetime will be exploited.

4 Conclusions

1) The obsolescence (technological progress) affects most components of industrial installations, particularly, the electronic and mechatronic components, but it is rarely investigated while devising at the engineering level for developing an approach.

2) A model is proposed, especially, in the case of challengers displaying less energy consumption rate and it allows the selection of the old-type components to be replaced.

3) The opportunity to speed up the replacement of the greater part of the old-type units by adapting the replacement criterion (budget).

4) This model can be applied in the case of a very large number of components.

5) The disadvantage of this model remains that it cannot always find the exact solution, but it always find a best solution, thus it is advisable to choose carefully the rules of the GA and to repeat the simulation several times.

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