OPERATING APPROACH FOR FLEET OF SYSTEMS SUBJECTED TO PREDICTIVE MAINTENANCE

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In this paper we present a new method which deals with the joint maintenance and assignment scheduling problem for a fleet of machines. The aim is to minimize the operation cost while satisfying a certain reliability level. For that purpose, we consider a non-homogeneous gamma process to model the degradation of the systems and estimate their reliability. Based on the reliability of each system, a decision-making algorithm is developed to reduce operation costs and to satisfy the forecasting demand. A Monte-Carlo simulation technique is used to evaluate the performance of the decision and to assess the risk level of the proposed scheduling. The proposed method is illustrated on numerical examples.

Keywords: Decision-making, Gamma process, Predictive maintenance, Reliability.

1. Introduction

Tasks scheduling plays an important role in manufacturing and transport systems [6]. It allows to plan the operation and maintenance of machines over a fixed horizon while satisfying certain constraints such as availability, resource limitations, etc. In order to respect all the constraints, the scheduling of tasks should take into account the degradation state of the related machines. Many approaches for joint maintenance and assignment scheduling have been proposed in the literature, which consider the remaining useful life as a key factor, see e.g. [3,5]. We here deal with the reliability indicator that is computed using a non-homogeneous gamma process, which is the more frequently used stochastic process for cumulative deterioration modeling (see [7,4] for a review on gamma processes). We recall

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that a gamma process $\boldsymbol{X} = (X_k)_{k \geq 0}$ is a stochastic process with independent increments, non-negative and gamma distributed such that $X_0 = 0$ almost surely. It is characterized by an increasing shape function $A(.)$ and a positive (constant) scale parameter B. In the sequel, we denote a non-homogeneous gamma process by $\boldsymbol{X} \sim \Gamma(A(.), B)$. The reliability function using gamma processes is given by :

$$R(k) = \mathbb{P}[\tau_L \geq k] = \mathbb{P}[X_k \leq L] = 1 - \frac{\Gamma(A(k), LB)}{\Gamma(A(k))} \quad (1)$$

where L refers to the failure threshold, τ_L is the failure time $\tau_L = \inf\{k > 0 : X_k > L\}$ and $\Gamma(A(k), LB)) = \int_{LB}^{\infty} s^{A(k)-1} e^{-s} ds$ is the incomplete gamma function.

In general, the selected degradation model of a machine is independent from its operating mode. This can lead sometimes to a wrong modeling and non-usable operation planning (see [2] for an example on the possible consequences on the performance of a maintenance strategy when using an erroneous deterioration model). In this paper, we propose a way to overcome the latter problem, which consists in combining the operation scheduling approach and the degradation modeling. For that purpose, we first develop a decision-making algorithm that performs jointly the maintenance and assignment scheduling. Then we estimate the parameters of the degradation model as well as the associated reliability, based on the information given by the manufacturer. This estimation will be used as an input for the decision-making algorithm that provides a new operating planning. The proposed approach is assessed through the effective reliability and cost functions.

The remainder of this paper is organized as follows. In section 2, the considered problem is presented. Section 3 describes the proposed decision making algorithm. Finally, the simulation strategy and the numerical example are given, respectively, in sections 4 and 5.

2. Problem statement and assumptions

The application in this paper is based on a fleet of $m_i, i = 1, \ldots, M$ machines used to satisfy a forecasting demand represented by N_k tasks for each discrete periods indexed $k = 0, 1, \ldots, K$, where K is the simulation horizon. Each type of task $\boldsymbol{T^{(j)}} = (T_k^{(j)})_{k \geq 0}$, for $j = 1, 2$, is associated to a degradation rate $\boldsymbol{D^{(j)}} = (D_k^{(j)})_{k \geq 0}$ generated by a gamma process $\Gamma(k^{\alpha_j}, b_j)$, with $\alpha_j > 0$ and $b_j > 0$. Once the N_k tasks are affected, the degradation model of the machines is constructed based on the degradation rate of the performed tasks. The degradation process of a machine m_i is denoted by $\boldsymbol{X^{(i)}} = (X_k^{(i)})_{k\geq 0}$ wth $i = 1, \ldots, M$. The failure of the machines is declared when their degradation level reaches a fixed failure threshold L:

- If $X_k^{(i)} \geq L$, the machine is failed and it is correctively repaired.
- If $X_k^{(i)} < L$, the machine can perform other tasks but it is possible to advance their maintenance in order to meet future demand.

We here assume that the degradation process of the machines is modeled by a gamma process defined in Section 1. The problem addressed here is how to manage the wrong modeling of the degradation and adjust it over time while satisfying the demand and the resource limitations. Before describing the approach, we present our assumptions :

A_1. A machine receives a slight degradation, even if it is not assigned to a task.
A_2. The maintenance resources are supposed to be enough to satisfy all the needed interventions.
A_3. The duration of corrective and predictive maintenance is respectively one and two periods of time (e.g. one day and tow days).

3. Decision making algorithm

We now introduce the decision making algorithm which deal with two sub−problems: Assignment and Planning. The first sub-problem concerns only one period while the second one concerns a defined planning horizon. For this reasons, two types of horizons are defined below:

- Simulation horizon K: It represents the total number of periods of the simulation.
- Planning horizon H: It corresponds to the windows of time in which we make a maintenance planing and missions assignment.

To deal with the mentioned sub-problems two algorithms are developed: assignment algorithm and planning algorithm. The first one (see Algorithm 1) is used to make the assignment of tasks for machines for one period. The objective is to guarantee a periodicity between the degradation level of the machines for a better maintenance actions distribution in the time. The ideal difference between the degradation level is defined by :

$$Id = \frac{t_m}{M-1} \tag{2}$$

where M is the number of machines and t_m is the total needed time to maintain them.

Algorithm 1 Assignment Algorithm

Data:

$T_k \Leftarrow$ List of expected tasks in the period k;

Av $\Leftarrow$ List of machines that can accomplish at least one task;

Initialization:

- Send the machines that reached their end of life to maintenance;
- Assign to the most degraded machine m_i from **Av**, the most difficult task from T_k that can accomplish it;

X_{min} = The new degradation level of this machine;

while *($T_k \neq \varnothing$ and $\boldsymbol{Av} \neq \varnothing$)* **do**

  $m_i \Leftarrow$ The most degraded machine from **Av**;

  if *($\exists\, T_k^* \subset T_k \;/\; \forall T_k^{(j)} \in T_k^*,\ X_{k-1}^{(i)} + D_k^{(j)} - X_{min} \geq Id$)* **then**

    Assign the most difficult task $T_k^{(j)} \in T_k^*$ to the machine m_i;

    $X_k^{(i)} = X_{k-1}^{(i)} + D_k^{(j)}$; $X_{min} = X_k^{(i)}$;

    $T_k \Leftarrow T_k \setminus \{ T_k^{(j)} \}$; $Av \Leftarrow Av \setminus \{ m_i \}$;

  else

    $Av \Leftarrow Av \setminus \{ m_i \}$;

  end

end

The second algorithm (see Algorithm 2) consists in using Algorithm 1 to make an operation planning during a planning horizon H. If there are some unsatisfied tasks, then advanced maintenance actions are programmed in order to increase systems availability. Consequently, Algorithm 1 is used again to make a new schedule that meets the constraints imposed in the previous step. This communication is repeated until the satisfaction of all the tasks or the absence of any opportunity to advance maintenance actions.

4. The adjustment approach of the degradation model

In order to check the performance of the proposed method, a case study is generated. We assume that the demand arrival follows a Poisson distri-

Algorithm 2 Operation Planning Algorithm

Data:

K : Simulation horizon; Pl_t**:** The planning of the instance t;

Pl_{t-1}**:** The planning of the instance t-1;

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for r ← 1 to K do
    - Use Algorithm 1 to assign tasks for the next H periods;
    - Pl_t ⇐ The assignment planning; Pl_{t-1} ⇐ ∅;
    - Lost ⇐ List of lost missions for each period k ∈ [r , H+r];
    while (Pl_t ≠ Pl_{t-1} and ∃ k ∈ [r, H + r]╲Lost(k) > 0) do
        for k ← r to H + r do
            D ⇐ List of system that can't accomplish tasks in the period k;
            while (D ≠ 0 and Lost(k) > 0) do
                m_i ⇐ The most degraded machine from D;
                if (m_i is available in one of the k − 1 periods) then
                    Program advanced maintenance for m_i in the period just
                      before k in which the machine is available;
                end
                D ⇐ D \{m_i};
            end
        end
        - Use Algorithm 1 to make a new assignment planning that respect
          the advanced maintenance actions;
        - Pl_t ⇐ The new assignment planning;
        - Pl_{t-1} ⇐ The previous assignment planning;
        - Lost ⇐ List of lost missions for each period k ∈ [r , H+r];
    end
    - Apply the planning of the period r;
end
```

bution $P(\lambda), \lambda > 0$, and we suppose that the degradation rate of each task obeys a gamma process (see Section 2). Tasks are assumed to be different each day and to induce degradation on machines equal to their degradation rate. If the degradation level $X_k^{(i)}$ of the machines m_i is smaller than L, any machine can be assigned to any task $T_k^{(j)}$ that satisfies $X_k^{(i)} + D_k^{(j)} < L$. Each performed task increase the degradation level of the machine until reaching L. In this case, a maintenance action is carried out to bring the system back to its initial state. During the simulation, machines are periodically inspected to measure their degradation. As mentioned in Section 2, the degradation of machines is modeled by a gamma process. Hence, its parameters are estimated using the Maximum Likelihood Estimation (MLE) techniques (see [1]).

The used methodology to adjust the degradation model and optimize the reliability and scheduling planning is divided in two steps (Offline and Online estimation): As a first step, the failure threshold (L_0) given by the manufacturer is used as an input for the planning tool (see Algorithm 2) to make an operation planning. Thanks to the MLE technique, the obtained degradation trajectories are used to estimate the parameters of the degradation model. At the end of this step, the estimated model is used compute the new reliability level and failure threshold. These parameters will be used as inputs for the second step (online estimation), which consists in repeating the same procedure of the first step until the most appropriate model is found. The simulation strategy is illustrated in the Figure 1 where $R_p(k)$ and L_p refer to the reliability and the failure threshold for the pth iteration.

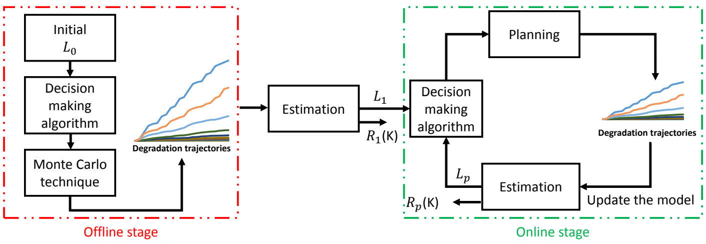

Figure 1. Adjustment approach of the degradation model

The aim of the proposed approach is to optimize an expected operation cost OC. This indicator takes into consideration the total costs of the different maintenance actions over the simulation horizon, which concerns the cost of lost tasks C_t, the costs of a predictive maintenance action C_p and a corrective maintenance action C_c:

$$OC = LT \times C_t + N_p \times (C_p + P_a) + N_c \times C_c \tag{3}$$

with LT is the number of non satisfied tasks and N_p, N_c are, respectively, the number of predictive and corrective maintenance actions. P_a represents a penalty associated to each advanced maintenance action which is equal to zero if the maintenance is performed in the correct period.

5. Numerical example and results

In this section we present a numerical illustration for the problem explained previously. We consider two types of tasks $\boldsymbol{T^{(1)}} \sim \Gamma(k^{0.5}, 2)$ and $\boldsymbol{T^{(2)}} \sim \Gamma(k^1, 1)$, where $k = 0, 1, \ldots, 100$. We fix also $C_p = 5$, $C_c = 10$, $C_t = 15$ and $P_a = 3$. At each period of time (day) the machines are assigned to satisfy $N_k \sim P(3)$ tasks of type (1) and (2). The degradation of 10 machines affected by the type of the performed tasks are displayed in Figure 2.

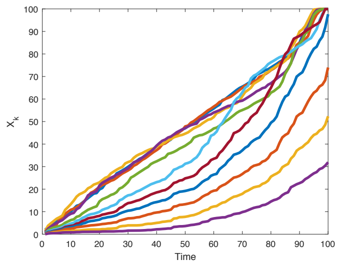

Figure 2. Levels of degradation of the fleet of machines over the simulation horizon

We set $L_0 = 100$ and initiate the offline stage (Iteration $p = 0$) of the decision-making algorithm. We then start with the online estimation from $p \geq 1$. Table 1 shows the results of the simulation strategy, where all computations are done using Monte-Carlo simulation with 500 repetitions. In this table, we display the failure thresholds L_p, the reliability $R_p(K)$ computed using Equation (1), the number of the performed predictive and corrective maintenance actions, the percentage of the non-satisfied (lost) tasks and the total operation cost OC.

Table 1. Summary of simulation results

p	L_p	$R_p(K)$	N_p	N_c	Lost tasks	OC
0	100	34.55 %	0	7	1.15 %	257.5
1	67	92.58 %	12	0	0.57 %	198
2	73	84.96 %	9	1	0.80 %	190.5
3	71	89.87 %	9	0	0.66 %	177
4	73	87.83 %	10	0	0.75 %	180

The presented results show that it is possible to satisfy the demand and adjust the model over time thanks to the proposed decision-making algorithm. This algorithm allows to reduce the percentage of lost tasks independently of the selected degradation model. Furthermore, the operation cost depends strongly on the quality of the selected degradation model but it can be optimized after a few number of iterations.

6. Conclusions and perspectives

In this paper, the non-homogeneous gamma is used to define an adjustable modeling for the degradation of a fleet of machines in line with their operation mode. The numerical application highlights the capacity of the proposed method to satisfy the demand even with a wrong modeling and to adjust the degradation model over the time until the most appropriate one is found and the operation cost is optimized.

This work should be seen as an initiation to future work, which is about providing a reliable operation planning. In this context, it would be interesting to look for some performance metrics that allow to quantify the uncertainty behind the degradation model and the proposed operation planning. Also, one could think about considering a random failure threshold at the beginning of each iteration. In addition, the proposed approach is limited in a real case since there is a lack of data for the offline procedure. More work should be done to overcome this drawback.

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