Modelling a production scenario under aging conditions

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Abstract: The mechanical design of a system component requires to consider several aspects which include the static, dynamic and thermal stresses, the order in which stresses follow each other over time, as in the case of material fatigue which generally does not adhere to the principle of superimposition of effects and, last but not least, the random features of the resistance of materials. Accordingly, well-known mathematical models and methodologies are used in the industrial practice. Conversely the knowledge of these phenomena is not exploited for the lifecycle evaluation of the operating status and residual life (for reliability and prognostic purposes) and, according to the most recent perspectives, the identification of cause-effect relationships based on the analysis of operating data (data driven), relying more and more often on the development of some kind of artificial intelligence, is preferred. Industrial plants, however, are made up of a considerable number of components which, despite being relevant for continuity of operations, are not equipped with such kind of technology that allows a continuous control due to their multiplicity and cheapness; as a result, the acquisition of that set of data which may be useful for the development of an artificial intelligence to improve maintenance and operations management appears very unlikely. This paper takes as use case of industrial component the electric motor to propose a model suitable for homogeneous classes of mechanical components, capable of evaluating the operating status of the environment-system control volume and therefore predicting the remaining useful life of a device when operating, environmental and performance conditions change continuously.

Keywords: stochastic hybrid automaton; predictive maintenance; scheduling.

1.Introduction

Production continuity of line of an industrial factory depends on several factors. Among them, the availability of the components constituting the production equipment is one of the most critical and important.

The availability of a system is the probability that it will operate satisfactorily over a given time horizon when used under stated conditions in an ideal support environment (Duarte, Craveiro and Trigo, 2016). The definition of availability includes corrective maintenance downtime and excludes those types of events which can be managed or included in the planning of the activities, like logistics time, waiting or administrative downtime, and preventive maintenance downtime (ISO/TR 12489:2013).

The availability of a system is analyzed during the conception and before the start-up of a system, in combination with the process specifications, in order to determine the main key-performance indicators that a system has to meet to fulfil the process requirements. It is also used as an input of the system design in order to identify criticalities and bottlenecks that can be caught and solved during the conception phase.

Traditional formalisms for the assessment of the system availability (Chiacchio, Iacono, D’Urso and Compagno, 2020) are based on mathematical and or simulation methodologies (Codetta-Raiteri and Portinale, 2014). The system and its processes are modelled and then solved according to the type of methodology adopted (Kabir, Yazdi, Aizpurua and Papadopoulos, 2018). As it can be understood, the output of these methodologies is able to provide a nominal indication on how the system would perform during its lifecycle; nevertheless, this indication is theoretical and may not reflect the real status of a system which, during its operations, is subjected to workload changes, or abnormal working conditions, that could not have been considered during the design phase.

Maintenance is defined as the combination of all technical and associated administrative actions intended to retain an item at/or restore it to a state in which it can perform its required function (ISO/TR 12489:2013). It is an important management activity because it can help to reduce downtimes and thus increase the availability of the system. It is possible to identity two main categories of maintenance: corrective maintenance operated as soon a failure has occurred and preventive maintenance which is performed according to different possible policies (testing, inspection, condition monitoring, periodic) to avoid a fault of the system.

One of the main limitations of these methodologies is that the models of the systems, the processes and the components interdependencies cannot be too complex. General track records of the components’

behaviors are often missing or have to be adapted from other use cases. In particular, this type of issue is very common for dated industrial plants and for the cheap components of an industrial machine that are not equipped with modern IOT sensors (Wu, Liu, Zhang, Terpenny, Gao, Kurfess and Guzzo, 2017).
Among the latter interdependencies it is necessary to highlight those that link production management and maintenance and how the results of the scheduling of operations can change according to the strategy used to guarantee a certain level of plant availability.
In the following, therefore, we will try to verify what are the results of the application of different scheduling rules while taking into account the contribution of the maintenance strategy adopted. The average cost of production and the production time required to process a production mix, over a defined time interval and taking into account how the variations in the characteristics of the processes affect the availability of the equipment used, is being studied.
The paper is organized as follows: section 2 presents the basic concepts of the problem addressed in this research. Section 3 describes the methodology and the mathematical tools which will be used in the experimental campaign, whose findings are discussed in section 4. In section 5 conclusions are drawn.

2.Problem statement

We analyze the medium-term planning of a production scenario involving a single failure prone machine; the failure mode analysis focuses only on the bearing system. The following factors may affect the performance of the manufacturing system under the reliability viewpoint: (i) the angular speed at which processing takes place; (ii) dynamic load transmitted to the bearings. Since the different parts to be processed require a different angular speed and exert a variable load on the bearings, the way jobs are scheduled may bias the failure mode of the manufacturing system and a series of turnaround measures as well (Baker and Trietsch, 2013) The characteristics of each job will be simulated by sampling them starting from a cumulative probability density functions associated with each fundamental characteristic mentioned above. The problem being analyzed therefore lies in the production scheduling related topic and makes use of makespan, total flowtime and average cost (involving production and maintenance cost) as key performance indicators. The nature of failures is linked to the aging of machine tool bearings; consequently, the maintenance strategy is preventive and characterized by a preventive maintenance period Tp, by unit costs of preventive and corrective maintenance.

3.Methodology

The production scenario just defined presents results that depend on the way in which the jobs are scheduled, on their technological characteristics and on the preventive maintenance period Tp that is chosen. The optimization of the problem just defined, even if the technological characteristics of the jobs to be produced are considered constant, requires the integration of the Weibull function which describes the probability density of failure of the bearings of machine tools. This integration is not easy; therefore, the solution of the problem will be searched by simulation of Monte Carlo (Wang, Zhang, Huang, Mourelatos, 2014). In the following it is therefore described how the modeling of the failure rate of machine tools and the scheduling of the production scenario is carried out.

3.1 Reliability modeling

Bearings have failure probability density which can be represented by a Weibull function; the failure rate (Kim, Kim, and Heo, G. 2018). Failure rate updates using condition-based prognostics in probabilistic safety assessments. Reliability Engineering & System Safety, 175, 225-233. and the cumulative probability that the bearing will fail before a certain time t, can be written as follows:

$$h(t)=(\beta/\alpha)\cdot(t/\alpha)^{\beta-1}. \tag{1}$$
$$F(t)=1-e^{-(t/\alpha)\beta} \tag{2}$$

where α is defined as expected or characteristic life and β is the shape factor.
As shown in (D'Urso, Chiacchio, Borrometi, Costa, Compagno, 2021) the experimental data published by SKF, allow to calculate the expected life, with cumulative probability of at least 90%, of a bearing of given dimensions, when subjected to known and constant stress conditions, in operating conditions of temperature To, and lubricant viscosity $\nu(To)$ still known and constant. We define, $L_{10,h}$ as the expected bearing life with a cumulated probability of 90% (h).

$$L_{10,h}=a_0\cdot n^{-1}\cdot(C/P)^p\cdot 10^6 \tag{3}$$

where:
n is the bearing angular speed *(rpm)*;
*C is the b*asic dynamic load rating *(N);* it depends on bearing type, geometry and lubrication*;*

P is the equivalent dynamic bearing load *(N);*

$a(T)$ is a correction coefficient that takes into account the variation of the operating temperature with respect to a reference value equal to 20 °C;

p is the exponent for the life equation ($p=3$ for ball bearings).

By combining equation (2) and (3) and setting $p = \beta$, it is possible to calculate the expected life of the bearing as a function of the operating conditions (angular speed n, operating temperature T, viscosity of the lubricant ν, stresses P, mechanical resistance of the bearing C). Therefore, the cumulative probability can be written as follows:

$$F(L_{10,h})=0.1=1-e^{-(L_{10,h}/\alpha)\beta}$$
$$\alpha=L_{10,h}\cdot ln(1/0.9)^{-(1/\beta)} = a_0\cdot n^{-1}\cdot(C/P)^p\cdot 10^6 \tag{4}$$

When the operating conditions change with respect to time, then equation (4) becomes a function of time together with the failure rate:

$$\alpha(t)=a(t)_o \cdot n(t)^{-1} \cdot (C/P(t))^p \qquad (5)$$
$$h(t)=(\beta/\alpha(t)) \cdot (t/\alpha(t))^{\beta-1} \qquad (6)$$

Once equations (5) and (6) have been obtained, it is possible to evaluate the time evolution of the failure rate by using the finite difference method; considered a discrete and little time bucket Δt, the elementary variation of the failure rate can be written as:

$$h(t+1)=h(t)+\Delta h(t) \qquad (7)$$
$$\Delta h(t)=h(t+\Delta t)-h(t) \qquad (8)$$
$$\Delta h(t)=[a(t+\Delta t)\, n(t+\Delta t)^{-1}(C/P(t+\Delta t))^p - a(t)n(t)^{-1}(C/P(t))^p] \qquad (9)$$

Fig. 1 shows the failure rate trend for a bearing with geometry and load conditions shown in table 1; the bearing is stressed following four load profiles; the first and second modes correspond to the application of a dynamic load equal to P1 and P2 respectively along a horizon H (P2>P1); the third and fourth modes are characterized by the permutation of the loads P1 and P2 each along the half of the horizon. It is shown that given the non-linearity of the cumulative damage, the order in which the stresses occur significantly influences the trend of the failure rate; the heavier stresses lead to lower failure rates if they are endured earlier. Fig. 1 again shows that the minimum failure rate over time does not always correspond to the same load condition. This implies that the preventive maintenance period and the order with which the stresses follow their self, affect the operating result of production management.

3.2 Job scheduling

The production scenario of a single machine batch problem is simulated taking into account the following hypotheses: (i) machine can process one job at a time; (ii) set-up times are not sequence dependent and are included in processing times; (iii) the release times of batches are different, but they are identical for jobs of the same batch. The discrete event simulation model is based on the following equations and constrains.

Let's define:

I the number of items;

N the mean overall item demand;

J_k the number of jobs for each item; J_k is random sampled $J_k = rnd : \Sigma_{k=1}^{I} (J_k)=N$;

b_j the batch composition; it is constituted by I elements of J_k jobs; $b_j=A_j \times [1;I] : \sum_{j=1}^{B}(a_{kj})=J_k \;\; \forall a_{kj} \in A_k,\ k \in [1;I],\ j \in [1;B]$

p_j the processing time for each job; it is uniformly distributed in the range *[pmin, pmax]* (see Table 2);

tr the time to repair in case of corrective maintenance; it is uniformly distributed in the range $[tr_{min}, tr_{max}]$ (see Table 2);

$a(T)$ the temperature corrective coefficient; it depends on the operative temperature according to the point to point relation of table 3; the operative temperature is modeled by means of a sinusoidal function: $T(t)=T_m+A\cdot sen(\omega_1 t+\phi_1)+B\cdot sen(\omega_2 t+\phi_2)$;
where T_m is the annual average temperature, ω_1 is the annual temperature frequency, ω_2 is the daily temperature frequency and A, B, ϕ_1, ϕ_2 are respectively the amplitude and phase of annual and daily temperature oscillation;

P_j the equivalent dynamic bearing load corresponding to each job; it is uniformly distributed in the range *[Pmin, Pmax]* (see Table 2);

n_j the angular speed corresponding to each job; it is uniformly distributed in the range *[nmin ; nmax]* (see Table 2).

C_c the cost of each corrective maintenance intervention; it is modelled summing a fixed (C_c) and a direct dependent from the time to repair t_r components:
$C_c=C_c+c_{var}\cdot t_r$ (see table 2).

C_c the cost of preventive maintenance (see table 2); it doesn't affect the job's flowtime because it is performed out of any daily production shift.

Tidle the overall lag of unavailability of the tool machine due to the maintenance interventions.
Table 2 refers all numerical values which were assigned to each problem variable.

Table 1: bearing principal features

Variable	Symbol	Value
Bearind external diameter (mm)	*De*	42
Bearing internal diameter (mm)	*Di*	30
Basic dynamic load rating (N)	*C*	4,490
Equivalent dynamic bearing load (N)	*P1*	2,000
	P2	2,500
Exponent for the life equation	*P*	3
Time horizon (h)	*H*	2,000
Angular speed (rpm)	*N*	1,000

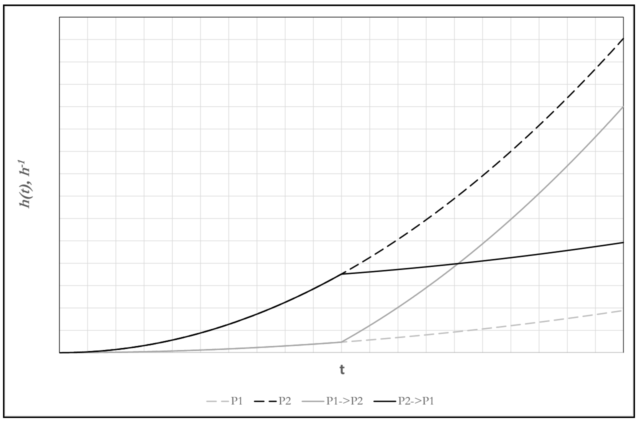

Figure 1: failure rate behaviour over time

Table 2: single machine production features

Variable	Symbol	Value
Overall item demand	*N*	2,000
Number of items	*I*	100
Number of jobs for each item	J_k	-
Number of batches	*B*	10
Release time for each job	*rj*	-
Processing time for each job	*pj*	[0.5; 3.33] h
Cost for preventive maintenance	*Cp*	5,000.00 €
Cost for corrective maintenance	*Cc*	5,000.00 €
Variable cost for corrective maintenance	*cvar*	[500; 1,000; 1,500] €
Time to repair (corrective maintenance)	*tr*	[1.5; 144] h
Overall time to repair (corrective maintenance)	*Tr*	-
Temperature corrective coefficient	*a(T)*	(-)
Basic dynamic load rating	*C*	4,490 N
Exponent for the life equation	*p*	3
Equivalent dynamic bearing load of each job	*Pj*	[400; 1600]
Angular speed for each job	*nj*	[1,000; 4,000]
Completion time for each job	*Cj*	-
Total idle time	*Tidle*	-
Number of preventive maintenance intervention	*np*	-
Number of corrective maintenance intervention	*nr*	-

Forty-five productions were simulated; all scenarios are defined according to five scheduling criteria, three preventive maintenance period (*Tp*) and three variable costs for corrective maintenance (*cvar*). As regard to the scheduling criteria, jobs are scheduled considering: (1-2) the bearing stress severity they perform; bearing stress severity is defined by the product of the requested angular speed, *n*, and equivalent dynamic bearing load, *P*; the less/more a job stresses the bearing system the earlier it is scheduled; (3-4) the shortest/longest processing time; (5) randomly.

Table 3: temperature corrective coefficient *a(T)* (lubrication ISOVG2, ν1=25 mm²/s)

T (°C)	ν	ν/ν1	*a(t)*
20	30	1,2	1
25	22.19692	0.887877	0.7333
30	17.35394	0.694158	0.4667
35	14.09353	0.563741	0.3333
40	11.76876	0.470750	0.2000

The scheduling criteria are in the following respectively mentioned as: *S*, *H*, *SPT*, *LPT* and *RND*.
Preventive maintenance period, T_p, is fixed respectively equal to 500, 1,250 and 2,000 h; the variable cost of corrective maintenance *cvar* is assumed respectively equal to 500, 1,000 and 1,500 €/h.
Measures used as output of the Monte Carlo simulation are below reported:

Makespan; $M=T_{idle}+T_r+max(C_j)$; $\forall j \in [1, N]$

Flowtime; $F=\sum_{j=1}^{N}(F_j)=\sum_{j=1}^{d}(C_j-r_j)$, $\forall j \in [1, N]$

Total cost of maintenance; $C=n_p\cdot C_p+n_r\cdot C_c+Tr\cdot c_{var}$.

4 Findings

Each schedule scenario is simulated along a 1,000 iterations process.
The makespan increases with the preventive maintenance period T_p and appears to be unaffected by any of the above-mentioned scheduling criteria (see fig. 2).

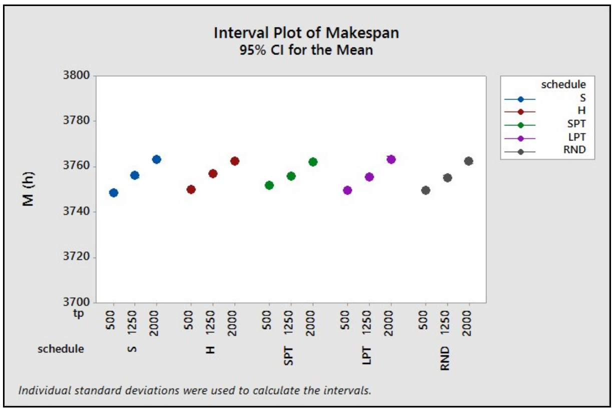

Fig.2 Makespan as a function of the preventive maintenance period T_p and scheduling criteria.

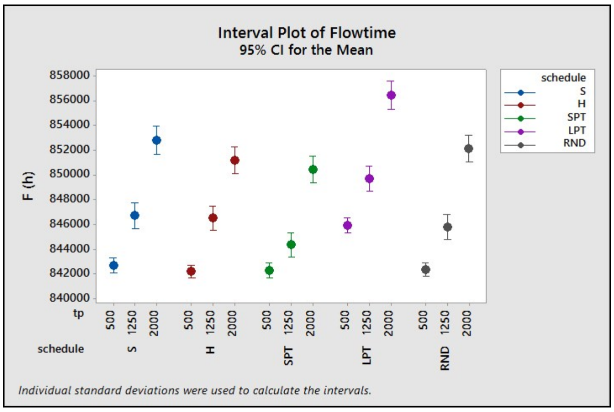

Fig.3 Flowtime vs the scheduling criteria.

The interval plots at 95% confidence level in Figure 3 shows a remarkable influence of both production strategy and preventive maintenance period *Tp* on the total Flowtime *F*. Reducing the maintenance period *Tp* positively affects the Flowtime measure, which strongly influences the in-process inventory, i.e., the work-in-process related cost (Baker and Triesch, 2013). As expected, conforming to the literature on the single-machine scheduling problem, the Longest Processing

Time (*LPT*) dispatching rule yields a detrimental effect the total flowtime, regardless of the *Tp* level assumed. Another interesting finding regards the production policies *S* and *H* since no significant difference emerges under the *Flowtime* viewpoint. Finally, the random scheduling strategy seems to be worse than *SPT*, specifically when *Tp* increases.

Figure 4 refers the total cost of maintenance, which finds almost always minimum value at *Tp*=1,250 h, independently from the other criteria. The random schedule enables the best tradeoff between preventive and corrective interventions balancing better jobs stress severity and machine tool aging. When the variable cost of corrective maintenance is set to the lowest value (*cvar =500*), a more frequent preventive maintenance (*Tp=500*) implies a higher maintenance cost than the one achieved by assuming a larger *Tp*.

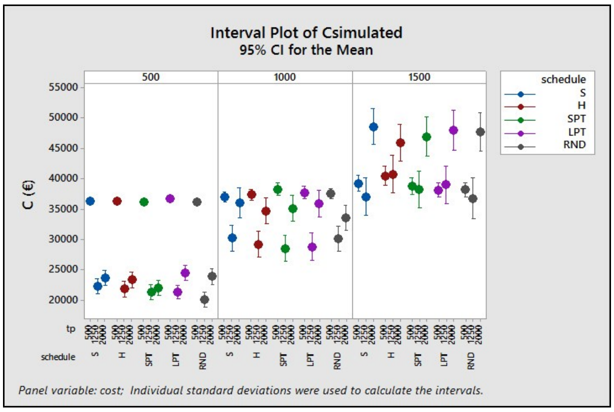

Fig.4 Overall maintenance cost along the schedule criteria and the cost of corrective maintenance.

In other words, since a few failures happen, the cost of preventive maintenance dominates the cost due to corrective. On the other hand, whether the variable cost component of the corrective maintenance grows (cvar >500), the effect of *Tp* on the total maintenance cost relatively reduces and for cvar =1,500 it emerges that the intermediate value of *Tp* (i.e., 1,250) represents the best compromise among the provided alternatives. Such findings can be justified by considering that a lower *Tp* generate a higher number of preventive maintenance interventions while a higher *Tp* yields a higher number of corrective maintenance actions.

Conclusion

We codified a model allowing to simulate results of the application of scheduling criteria on a productive single machine scenario considering how the operating and environmental conditions affect the failure behavior of the machine tool and how the maintenance strategy and production mix affect the operating result. The study, although at an embryonic stage, aims to enhance the short- and medium-term planning by taking into greater detail the environmental and operational conditions in which production operates, offering the contribution of stochastic hybrid automaton models to those of scheduling optimization. The contribution that the sensitivity analysis can make to determining the best compromise between the aspects is still significant.

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