Prognostic tools and predictive maintenance models for complex degrading technological units in the presence of multiple sources of variability.

Stochastic degradation models, residual reliability, remaining useful life, condition-based maintenance.

In recent years, the idea of using data collected in real time (for example sensor data) to implement decision-making strategies that could allow to optimize the overall performance of complex systems is gaining an increased interest. An objective of these models is the formulation of predictive maintenance strategies. Several challenges are still existing for the improvement and the use of such solutions. One of the tasks of maintenance optimization is the analysis and exploitation of the data or measurements collected by monitoring the state of the system and/or its environment. Here the challenges consist in analyzing large amount of heterogeneous data, performing early diagnosis about the state of health of the system, predicting its future evolution, and integrating all these pieces of information into a complex decision-making procedure.

The purpose of this research project is to develop new prognostic tools that can be used to perform more effective and better informed maintenance decisions.

Most of research on maintenance modelling is based on classical lifetime models. These models are usually estimated directly from failure time data. In fact, the standard statistical approach to lifetime distribution modelling consists in selecting a parametric model among a limited list of candidates and determining its unknown parameters. The candidates are usually prepacked black-box models. Model selection is done by means of goodness of fit tests and/or some considerations concerning the ability of the model to capture the aging characteristic of the system under study. Unknown parameters are estimated by using ad hoc inferential procedures. Both these tasks are usually performed based on failure
data only and the system condition during its operation period until failure is totally ignored. This approach is not always fruitful or, at least, it is not always effective. The main reasons for this inadequateness are the scarcity of failure data and the fact that it doesn't allow to directly use other kind of information and experimental data that are often available in the applications. In addition, depending on the context, the reliability model may be requested to have specific peculiarities, which standard black box models do not possess. Actually, in all these cases, it may be convenient to adopt different modelling solutions.

In fact, to overcome the limitations of classical approach a great part of the recent literature on maintenance optimization is focusing on the use of stochastic degradation process models.

The proposed research activity will address this latter aspect, aiming to the formulation, and use in maintenance planning, of stochastic processes that could guarantee the predictive performances requested to make effective maintenance decisions, taking advantage of all data and pieces of information available in real world applications.

**Experimental framework and motivation**

Many technological units are subjected, during their operating life, to a gradual degradation process that, in the long run, causes an inevitable situation of failure, which is (conventionally) assumed to occur when their degradation level passes a given critical threshold. Often these units are very costly and their operational failures produce relevant losses. Thus, to prevent failures, they are usually subjected to condition monitoring and condition-based preventive replacement. As a rule, the earlier is the preventive replacement the lower is the risk of failure. Nevertheless, any preventive replacement has a cost that is directly proportional to the residual life of the replaced unit (i.e., to the amount of operational life lost due to the preventive replacement). The crucial issue in this kind of practices is to identify the replacement time that provides the optimal tradeoff between preventive and corrective maintenance costs. The working principle is to delay the replacement until the risk of failure becomes intolerable. Actually, this task can be more challenging than expected. In fact, in many practical settings the continuous monitoring of degradation is not feasible. Thus, the state of the unit is checked only via periodic inspections. Moreover, the preventive replacement of the unit often requires special equipment and/or special skills. Thus (for example), the replacements can be performed only at specific epochs. This situation creates the need for models that are able to provide accurate predictions of the remaining useful life of the unit of interest, given the information available on its status. Concomitantly, while preventive maintenance (preventing failures) precludes the collection of failure data necessary to estimate the classical lifetime models, condition monitoring allows collecting a great number of degradation data, and maintenance activities provide a valuable insight into the failure causing mechanism.

All these circumstances make the idea of facing the discussed problem by using stochastic models able to describe the evolution of degradation over time particularly appealing and convenient. In fact, this approach permits, at the same time:

- to formulate models that can incorporate the technological information available on the degradation/failure causing mechanism (which that can be converted in specific features of the stochastic models)
- to use historical degradation data to perform estimation procedures and evaluate the fitting ability of the model, and
- to use the degradation data collected in real time, via condition monitoring, to implement the requested (condition-based) maintenance strategy.

Further challenges, in modelling degradation, consist in adopting modelling solutions that could account for the effect of (possibly randomly) changing environmental conditions.
Objectives and methodologies
The main objective of the project is to formulate maintenance models that can capitalize on all the available pieces of information and should have a simple mathematical structure.
In order to achieve this task, we will adopt the following three-step procedure:
• modelling the stochastic degradation process of the system under study;
• obtaining its reliability function as the distribution of the time at which the measured variables passes the failure threshold for the first time (i.e., by solving the first passage time problem);
• formulating the maintenance policy by taking advantage of the degradation based reliability model, that allows to treat in an explicit way the dependence of the remaining useful life on the status of the units (key issue in the addressed applications).
The maintenance models should allow the use of all the available pieces of information and should be able to account in explicit way for all the existing sources of uncertainty as well as on their effect on the degradation process and on the related maintenance model.
Actually, uncertainty on the estimation and prediction of the health state of a degrading unit can be caused by several sources. Some can be endogenous (for example, undetected differences among the units) other can be exogenous (e.g., randomly varying environmental conditions, which induces difference between degradation paths of identical units and influence their evolution over time). Other sources of uncertainty are the presence of measurement error and/or the fact that monitoring system itself can be subjected to a degradation process.
The attention will be thus devoted to degradation and (related) maintenance models that can (explicitly) account for the presence of all these kind of uncertainties, in order to evaluate their effect on the condition based decision strategy.
It is worth to note that the presence of random effect, randomness in the operational environment, and/or measurement errors (and/or noise) leads to the loss of some mathematically convenient properties (e.g., independence of increments, stationarity of increments, Markovianity) of stochastic models that can be used to analyze the data. This situation exacerbates both modelling, inferential, and computational issues that are (already) usually encountered in this kind of applications. For example, the presence of measurements error prevents from observing the true state of the system. In this experimental situation, both inferential procedures and condition-based prediction of the future state of the system become more challenging. Hidden Markov Theory, Sequential Monte Carlo Methods, Expectation Maximization algorithms are among the theoretical tools that allow to tackle these issues. Obviously, the maintenance model and the inspection strategy are impacted by the presence of these issues. Hence, decision framework and maintenance decision rules should be revised accordingly.
Regarding the application aspects, we will mainly focus on the case of energy production systems, in particular those relating to renewable energies. These systems are subject to very changing environmental and operating conditions (wind, temperature, solar radiation, etc.). In addition, energy demand varies randomly over time, and to ensure a regular, loss-free, production, the way the system operates must also vary. Under these conditions, it is important to be able to estimate the residual life of the system at any time and throughout its operational life. To accurately estimate the residual life it is necessary to analyze the monitoring and rest data in a complete, efficient and rapid way and model the behavior of the system on the basis of these data. During monitoring, system health indicators are extracted from the available data. Modeling the evolution of these indicators over time, for example the evolution of the length of a crack appearing on a wind turbine blade, allows the remaining useful life of the system to be predicted. Given the random and dynamic aspect of the evolution of system health indicators and considering the influence of environmental and operational conditions on their evolution over time, probabilistic models, more precisely stochastic processes, appear good candidates to describe their behavior. In this project we will consider the modeling of the degradation of a multicomponent system, with multiple failure modes,
in the presence of stochastic dependence. The impact of environmental conditions will be accounted for by incorporating into the basic model appropriate covariates. The degradation of each component will be described by an increasing monotonous process. It will be assumed that, depending on their mutual position, the degradation and failure of the considered components may affect the degradation of the other components. A competing risk model will then be proposed and the problem of estimating the model parameters and the residual life of the considered systems will be studied.

The degradation model will be finally used to define a optimal condition based selective maintenance plan policy for the complex system.

Relevance to the MERC PhD Program (max 2000 characters)

Predictive maintenance is nowadays a major concern for optimizing and controlling complex systems. It is one of the main topics that is promoted in the context of industry digitalization and the advent of the Industry 5.0. This is reflected today in a real commitment between industries and academic researchers. Indeed, the fact that manufacturers are aware of the data's exploitation potential and in particular their interest in a maintenance framework – that has for too long been the poor relation in the search for industrial performance – has led them to look at the results and models produced in an academic context and, conversely, for researchers to draw inspiration from complex industrial real-case problems. The project is relevant to the MERC PhD program in all its part, concerning the assessment and the mitigation of the risk of failure of complex technological systems by means of stochastic models that allow to estimate and predict the evolution of phenomena whose dynamic cannot be captured by deterministic models. The project also requests an interdisciplinary approach. Indeed, although their research interests are similar, the partners involved in the project have a quite different scientific background.

Key references

- Jumeau numérique et maintenance prédictive - https://www.mobility-work.com/fr/blog/jumeau-numeriquemaintenance-predictive-combo-gagnant


• Esposito N, Castanier B, Giorgio M. (2022), Impact on performances of a condition-based maintenance policy of misspecification of gamma with inverse Gaussian degradation process, In Proc. of the 8th Intl. Symp. on Reliability Engineering and Risk Management (ISRERM 2022), 4-7 September 2022, Hannover Germany,


Location and length of the study period abroad (min 12 months)

The PhD student will spend 6 months at the University of Angers (FR) and 6 months at the Aix-Marseille University (FR). The student is expected to travel abroad during the second and third year of his PhD program.

We are also considering the possibility that the PhD student could prepare a co-directed thesis (in this latter case he will receive two PhD degrees, one awarded by the University of Naples and one awarded either by the University of Angers or by the Aix-Marseille University).

Joint supervision arrangements

PhD student will be co-supervised by Profs Giorgio, Castanier, and Fouladirad. The student will spend six months in Angers and six months in Marseille, under the direct guidance of profs. Castanier and Fouladirad, respectively. Monthly progress meetings will be done through reports and weekly meetings will be done in telematic mode.

Any other useful information

If needed, we have the possibility of involving in the project other an industrial partner. We plan to apply to the Vinci program to obtain funds for mobility. Other funds will be requested to the University of Naples Federico II, as a contribution for the activities carried out with the University of Angers (within an existing formal agreement that involves the Profs Giorgio and Castanier) and Marseille (within a formal agreement, in preparation, that will involve the Profs Giorgio and Fouladirad).

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