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A combined sensitivity analysis and kriging surrogate modeling for early validation of health indicators

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ABSTRACT

To increase the dependability of complex systems, one solution is to assess their state of health continuously through the monitoring of variables sensitive to potential degradation modes. When computed in an operating environment, these variables, known as health indicators, are subject to many uncertainties. Hence, the stochastic nature of health assessment combined with the lack of data in design stages makes it difficult to evaluate the efficiency of a health indicator before the system enters into service. This paper introduces a method for early validation of health indicators during the design stages of a system development process. This method uses physics-based modeling and uncertainties propagation to create simulated stochastic data. However, because of the large number of parameters defining the model and its computation duration, the necessary runtime for uncertainties propagation is prohibitive. Thus, kriging is used to obtain low computation time estimations of the model outputs. Moreover, sensitivity analysis techniques are performed upstream to determine the hierarchization of the model parameters and to reduce the dimension of the input space. The validation is based on three types of numerical key performance indicators corresponding to the detection, identification and prognostic processes. After having introduced and formalized the framework of uncertain systems modeling and the different performance metrics, the issues of sensitivity analysis and surrogate modeling are addressed. The method is subsequently applied to the validation of a set of health indicators for the monitoring of an aircraft engine's pumping unit.

1. Introduction

Over the past decade, enhancing dependability has progressively become one of the main challenges for many industries, especially in the field of aeronautics. Indeed, a considerable portion of the average operating expenses of airline companies is attributable to maintenance, repair and overhaul (MRO) and delays and cancellations (D&C). These expenses are of two types. The first type includes the costs generated by regularly scheduled MRO operations, and the second are those generated by unexpected MRO operations. The expenses associated with the latter can be very high in certain situations, such as when a failure occurs in an isolated, poorly equipped airport. In this situation, additional expenses are generated because of spare parts delivery, aircraft immobilization and passenger indemnification. If the expenses related to regular maintenance are irreducible because they are derived from certification authorities, the other expenses could represent a source of significant savings if one could achieve increased dependability. It is for this reason that industries are increasingly more interested in failure anticipation and real-time maintenance strategy optimization.

To predict failures and schedule supervised maintenance, a new field of research, prognostic and health management (PHM), has gradually emerged over the past decade as the unavoidable solution. This new field is receiving much attention from the research community, as evidenced by [1–3] and references therein. PHM is based on the monitoring of relevant variables reflecting the different degradation modes likely to occur in the system. These relevant variables are termed health indicators (HIs). A classical PHM framework usually performs detection, identification and prognostic. While different forms of the PHM process can be found, the most commonly used, at least in the industry, is the open-structure architecture for conditioned based maintenance (OSA-CBM) scheme [4]. Although PHM is a quite recent discipline, it has reached a certain maturity with the development of its own standards, as shown in [5,6]. It has also been frequently applied and has demonstrated good results, first in its original field of application, structural health monitoring (SHM) [7], and later, in other fields, such as bearing monitoring [8] and battery life prediction [9]. The present work is dedicated to the monitoring of

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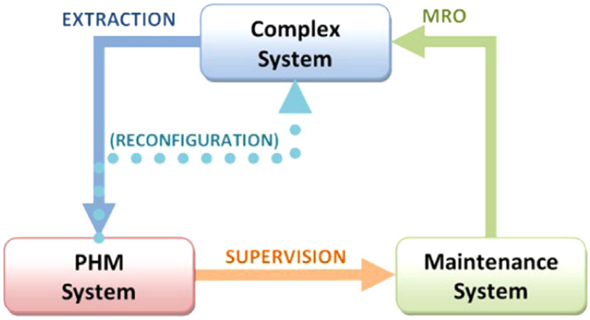

Fig. 1. Interaction scheme between the complex system, the PHM system and the maintenance system.

multi-physics complex systems with closed loop control, which is a novel and relatively unexplored application of PHM.

A PHM system can be defined as an entity interacting, on the one hand, with the complex system via an extraction process and, on the other hand, with the maintenance system via a supervision process (see Fig. 1). The purpose of the extraction process is to provide the set of HIs to the PHM system. The purpose of the supervision process is to assess the current health status of the complex system, to predict its evolution and to propose corrective or predictive actions to maintenance operators.

Whereas the supervision framework is the subject of many papers, the extraction framework is rarely addressed because its complexity is often underestimated. Indeed, at first glance, the extraction simply consists of recording data, but the real difficulty is to determine which data are to be recorded. Even if some research has been conducted to define certain generic methods for constructing HIs, such as parity space [10], most of these methods are not adapted to overcome certain challenges, such as uncertainties, imposed sensor numbers and locations, limited computation capabilities and prohibitive controller retrofit costs [11]. Thus, when an actual system is considered, it is necessary to perform a complete knowledge analysis to determine critical degradation modes and to construct relevant physics based HIs that are compatible with the sensor's configuration and the computation capabilities. These HIs also must be validated before the system enters into service because of the controller retrofit costs. This last point is the most critical because PHM processes are inherently stochastic problems, and it is obviously difficult to validate something stochastic before the availability of measured in-service data.

To overcome this lack of data for the validation of HIs, numerical modeling associated with a complete management of parameters uncertainties [12] is used during design stages to simulate the HIs distributions with and without degradations. This operation requires a good knowledge of input uncertainties, which is usually acquired through expertise and experience feedback from similar systems. Once both the healthy and faulty distributions of HIs are computed, some numerical key performance indicators (NKPIs) are computed to quantify the quality of the HI set in terms of detection, identification and prognostic potential. In the aeronautic industry, the NKPIs could account for a major step forward as online data recording is very expensive.

However, the propagation of uncertainties presents two major issues. First, in cases where the physics-based model is defined by numerous parameters, the quantification of uncertainties can rapidly become very time-demanding and expensive because it needs to collect much knowledge from various sources. Then, when the simulation runtime of the physics-based model is important, for example, several minutes or hours, the computation time required for uncertainties propagation becomes prohibitive. This is all the more true as the PHM system is composed of numerous HIs and numerous degradation modes. This paper proposes to use a combination of sensitivity analysis techniques and kriging surrogate modeling to solve both issues. Sensitivity analysis is performed in two stages. First, after having roughly determined the variation range of parameters, the Morris method is used to achieve a reduction in the parameters' space dimension. This allows for determining the set of uncertain parameters that will be the inputs of the kriging model. The computation of Sobol indices is then performed to hierarchically sort the uncertain parameters with respect to their effects on outputs. From this hierarchization, we identify the most influent parameters on which the fine uncertainties quantification are targeted. Kriging is used to obtain a low computational cost function for estimating the model outputs. Due to the reduction of input space provided by the sensitivity analysis, the size of the learning design of experiments is significantly reduced. Finally, both the computation of Sobol indices and uncertainties propagation can be run on the kriging model at reasonable computation time costs. Finally, the efficiency of the whole method is tested on a real complex system, namely, the pumping unit of an aircraft engine fuel system.

The remainder of the paper is organized as follows: In Section 2, the background of uncertain systems modeling are addressed through specific definitions of key terms. The numerical key performance indicators for HI validation in design stages are then introduced. The Sections 3 and 4, respectively, are dedicated to the sensitivity analysis and the surrogate modeling. Finally, Section 5 introduces the application system, and Section 6 presents and discusses the results.

2. Uncertain systems modeling

In [13], uncertainty is defined as "the incompleteness in knowledge and the inherent variability of the system and its environment". In this section, the modeling of a complex system $\mathfrak{S}$ accounting for uncertainties is addressed through specific definitions of key terms

2.1. System modeling

2.1.1. Numerical model

We propose to represent the determinist model of a complex system by the function f:

$$\boldsymbol{Y} = f(\boldsymbol{U}, \rho_1, \dots, \rho_p) \tag{1}$$

where $\boldsymbol{U}$ is the matrix of the model inputs, $\boldsymbol{Y}$ is the matrix of the model outputs and $\rho_1, \dots, \rho_p$ are the model parameters. As the numerical model is a discrete system, considering a sample period equal to T and a simulation of k samples, the input and output matrix is written as follows:

$$\boldsymbol{U} = \begin{vmatrix} u_1(0) & \dots & u_n(0) \\ u_1(T) & \dots & u_n(T) \\ \vdots & \ddots & \vdots \\ u_1((k-1)T) & \dots & u_n((k-1)T) \\ u_1(kT) & \dots & u_n(kT) \end{vmatrix} \in \mathbb{R}^{k \times n};$$

$$\boldsymbol{Y} = \begin{vmatrix} y_1(0) & \dots & y_m(0) \\ y_1(T) & \dots & y_m(T) \\ \vdots & \ddots & \vdots \\ y_1((k-1)T) & \dots & y_m((k-1)T) \\ y_1(kT) & \dots & y_m(kT) \end{vmatrix} \in \mathbb{R}^{k \times m} \tag{2}$$