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Diagnostic / Prognostics Strategies Applied to Physical Dynamic Systems: a Critical Analysis of Several Model-Based Fault Identification Methods

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Abstract. The development of adequate diagnostic/prognostic methodologies, suitable to provide a timely and reliable evaluation of the health status of a given system on the basis of some representative parameters (measured in a direct or indirect way), is fundamentally started in engineering fields, but, especially in recent years, it is encountering more and more interest and application in many technical fields and nowadays it represents an important task in various scientific disciplines. The health status of a given dynamic system (e.g. environmental, mechatronic, structural, etc.) and the eventual incipient failures that concern it, especially if related to progressive evolutions, can be identified and quantified by means of different approaches widely described in the literature. It must be noted that, particularly in recent years, there has been a strong impulse in the development of strategies aimed to design prognostic algorithms able to identify precursors of the progressive failures affecting a system: in fact, if it is correctly identified the degradation pattern, an early warning can be triggered, leading to proper corrective actions (i.e. proper remedial or maintenance tasks, replacement of the damaged components, etc.). Since these algorithms are strictly technology-oriented, they can show great effectiveness for some specific applications, while they may fail for other applications and technologies: therefore, it is necessary to properly conceive the specific prognostic method as a function of several parameters such as the given (dynamic) system, the available sensors (physical or virtual), the considered progressive failures and the related boundary conditions. This work proposes a critical comparison between several diagnostic/prognostic strategies in order to put in evidence their strengths and the eventual shortcomings.

INTRODUCTION

Nowadays the analysis of complex dynamic systems (e.g. environmental, thermochemical, mechanical, electronic, mechatronic) disposes of many tools to study their peculiarities, identify their characteristic parameters, study their evolution or highlight abnormal or undesired conditions in a timely manner. Numerical modeling and simulation techniques, combined with more powerful and effective methods of signal analysis and evaluation of the characteristic parameters, allow the development of new analysis and monitoring tools based on the comparison between the real system and the corresponding numerical model (assumed as the reference of the real one and operating as a monitor). This approach, commonly defined as "model-based", is widely used in engineering disciplines, but can also find effective applications in many other technical-scientific fields.

In particular, the development of adequate diagnostic and prognostic (D/P) methodologies, suitable to provide a timely and reliable evaluation of the health status of a given system on the basis of some representative parameters (measured in a direct or indirect way), is an important issue in several engineering fields, but, especially in recent years, it is encountering more and more interest and application in many technical fields and nowadays it represents an important task in various scientific disciplines.

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Diagnostics main goal is the identification of the nature and cause of a certain phenomenon affecting the monitored system; it is used in many different disciplines with variations in the use of logic, analytics, and experience to determine "cause and effect"; in systems engineering and computer science, it is typically used to determine the causes of symptoms, mitigations, and solutions [1].

Prognostic has been developed in engineering fields and, in these contexts, its main purpose is to predict when a certain component loses its functionality and is not further able to be fully operative or to meet the desired performances. Such a discipline is based on the analysis and comprehension of all the possible failure modes and on the capability of individuating the first symptoms of aging or wear. Once properly gathered and organized, such a database can be effectively used as an input of a proper failure propagation model. As for the other technological domains, applying prognostics to system engineering (e.g. industrial, mechanical or aerospace fields) could have a beneficial impact on safety and maintenance aspects, as it could reduce risks of unexpected system conditions, maintenance costs and inspection time; the goal of this discipline, named Prognostics and Health Management (PHM) [2-3], is to provide real-time data of the current status of the system and to calculate the Remaining Useful Life (RUL) before a fault occurs with the consequence that a component becomes unable to perform its functionalities at the desired level. For instance, referring to aeronautical onboard application field, the advantage of implementing PHM clearly emerges from the comparison with classical monitoring and maintenance concepts, based on overhaul or life-limited parts (e.g. primary flight controls are a critical part of the aircraft system and are therefore designed with a conservative safe-life approach, which imposes to replace the related components after having endured a fixed amount of flight hours or operating cycles; as reported in [4], by applying PHM strategies failures could be managed in a more effective way, reducing risks and criticalities and gathering several benefits in terms of costs, effectiveness and efficiency). It must be noticed that the said diagnostic and prognostic concepts, because of the variety of applications and the huge impact that they generate, have aroused great interest in the scientific and technological world and, especially in recent years, have been the subject of extensive development and dissemination in the scientific literature. Very often these contributions, despite being extremely innovative and significant, result too theoretical or specific and tend to overlook a more comprehensive approach (i.e. systemistic vision), dwelling on well-defined and circumscribed aspects of the considered problem.

In accordance with the aforesaid considerations, this work proposes a critical comparison between several diagnostic/prognostic model-based strategies to put in evidence their strengths and the eventual shortcomings. In order to briefly compare the different approaches, highlighting the main criticalities and evaluating their performance authors will refer to a test case derived from aeronautical systems that, although referring to a very specific application and, therefore, being a little distant from the general theme, will allow to illustrate the different methods in a clearer and a more applicative way.

D/P MODEL-BASED METHODS

The health status of a given dynamic system (e.g. environmental, mechatronic, structural, etc.) and the eventual incipient failures that concern it, especially if related to progressive evolutions, can be identified and quantified by means of different approaches. It must be noted that, particularly in last decade, there has been a strong impulse in the development of strategies aimed to design prognostic algorithms able to identify precursors of the progressive damages/faults affecting a system: indeed, if it is correctly identified the degradation pattern, it is possible to perform a Fault Detection and Identification (FDI) [5], i.e. identify the unexpected/undesired effects and quantify their magnitudes, and an early warning can be triggered, leading to proper corrective actions (i.e. proper remedial or maintenance tasks, corrective actions to reduce the harmful effects of certain events, phenomena or activities, replacement of the damaged components, etc.). In literature, many different FDI methods have been investigated: model-based techniques based on the direct comparison between the output of real and monitoring system [2, 6-8], on the spectral analysis of well-defined system behaviors performed by Fast Fourier Transform [9-10], on combinations of these methods [11] or on Artificial Neural Networks [12-15].

Since these algorithms are strictly technology-oriented, they can show great effectiveness for some specific applications, while they may fail for other applications and technologies: therefore, it is necessary to properly conceive the specific D/P method as a function of several parameters such as the given (dynamic) system, the available sensors (physical or virtual), the considered progressive failures and the related boundary conditions. Then it is necessary to carefully analyze the considered system in order to identify the fundamental relationships that characterize its dynamics and, therefore, to formulate a numerical model capable of simulating its dynamic behavior.

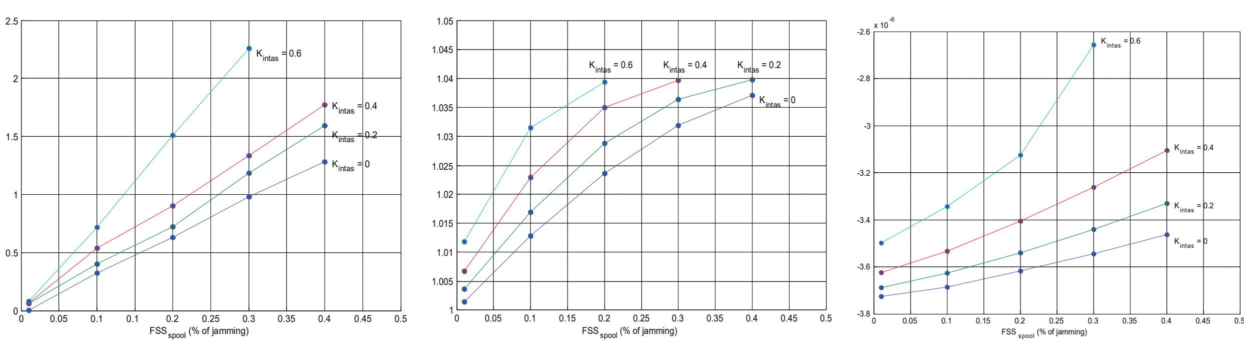
This model can be implemented in different ways, e.g. mathematical model obtained from its physical relationships, simplified best-fitting models, cause-effect relationships, identification methods, integration of experimental data or empirical relations, approaches hybrids obtained by combining the previous ones. In this phase, it is necessary to evaluate the effects due to the considered faults / anomalous conditions on the system response, in order to identify the eventual precursors of failures [5] and to define proper test cases suitable to perform the said FDI analysis [8,10]. It should be noted that this model must be appropriately tested and validated in order to verify its fidelity and robustness and, especially if designed for monitoring or FDI activities, it is necessary to verify its ability to accurately simulate the behavior of the system in the presence of the aforementioned failure modes.

The so obtained monitoring model (MM), sensitive to the considered failures and to any significant boundary conditions, can be used to estimate the health status of the system on the base of different approaches that will be briefly described in the following.

Fault Maps Method

A first method for estimating the health status of a system, particularly effective when the faults considered are few and they are relatively independent of each other, is that based on the so-called "fault maps" (FMs) [8, 10].

A fault map constitutes the graphical representation of how a system-representative parameter varies as a function of different types of faults. In other words, if the measurement of the real system parameter is available, this instrument allows supposing which extent a certain couple of faults has on the actuator. More exactly, a fault map displays the first fault G_1 on x-axis and the representative parameter P_1 (i.e. a systems characteristic assumed as failure precursor) on y-axis. Each map represents a set of curves $P_1 = f(G_1)$ that is parameterized with the a second fault G_2. A proper choice of P_1 is crucial in order to obtain a useful fault map. In the first place, this parameter should be a function of both G_1 and G_2 and be highly sensitive to changes in fault levels. In particular, its dependence from the two kinds of fault should be monotonic, i.e. the curves plotted on the maps should not intersect. The last feature is the most important, since it allows detecting a specific area on the map containing all the possible fault levels. However, the proposed method, in order to identify the system conditions with high enough accuracy, requires more than one of these maps for a specific couple of faults. It must be noted that, when several maps are employed, they have to be independent from each other: in this way, the parameter represented on each map is a magnitude that is not related to the others. By using three independent maps, i.e. representing three different parameters P_1, P_2 and P_3, an accurate area containing the possible faults is identified (Fig. 1).



(a) (b) (c)

FIGURE 1. Example of FMs referring to the example shown in [10]: these maps report the evolution of the three failure precursors P_1, P_2 and P_3, calculated respectively, for different values of the two considered progressive faults (FSS_{spool} and K_{intas}).

This FDI method is relatively simple, not expensive for the processor and fast enough (reduced CPU time) but requires a rather complex and expensive preparation phase, where it is necessary to define the FMs by comparing the responses of the real system with those of the corresponding MM for various combinations of faults. In fact, in order to calculate the above FMs, it is necessary to acquire the responses of the physical system for different combinations of faults and then, comparing them with the corresponding response of the MM, to calculate the relative fault precursors. It is clear that this experimental acquisition can be rather expensive, both in economic and in chronological terms. Furthermore, compared to other methods, this approach does not allow for a very detailed FDI but rather a relatively coarse classification of faults.

Evolutionary Algorithms

Several optimization techniques are commonly used also for model parameter estimation tasks, which can be classified into two main categories: deterministic (direct or indirect) and probabilistic (stochastic, as the Monte Carlo method, simulated annealing and genetic algorithms). As reported in [10], a large part of these methods are local minima search algorithms and often do not find the global solution (i.e. they are highly dependent on a good initial setting). Local-minima approaches would not be robust and may provide a false indication of parameter changes in an on-line system (i.e. a wrong selection of starting settings could determinate problems of convergence or global minima). Otherwise, global search methods, such as genetic algorithms (GA) and simulated annealing (SA), provide more promising options for on-line model identification [6-7].

Starting from these considerations, it is possible to develop model-based FDI methods, able to identify fault levels of a given system, analyzing its dynamic response and comparing it, through a process of optimization, with the response generated from a corresponding numerical model. Then, the proposed approach to detect these faults is based on the comparison of two signals coming respectively from the reference system (RS) and the monitor (MM). It should be noted that the latter is a simplified model with the requirement to be simple and fast in terms of implementation and computational time, since these methods needs several iterations, making the heavily detailed model inappropriate. The comparison between RS and MM is performed by an optimization algorithms that aim to minimize proper fitness functions [16] (e.g. a quadratic error function) by changing iteratively one or more parameters (defined as representative of the examined faults) of the monitor model until the output signal best overlaps with the reference system response. If the parameters calculated by the optimization algorithm match with the real ones, the method has worked properly; if the monitor model is accurate enough, the optimization algorithm gives a good detection of the system health. Operationally speaking, the parameters so obtained (relative to the MM) can then be correlated to the corresponding progressive failure (affecting the RS) in order to perform the aforementioned FDI. The optimization process is usually governed by means of Genetic Algorithms (e.g. see [16]) or other evolutionary systems such as Simulated Annealing [17-20], MS-ABC [21], Cuckoo Search [22], Firefly Algorithm [23], etc. In this paragraph, to clarify the different methods, the author will now refer to GA and SA.

Genetic Algorithms

As previously mentioned, the optimization process used to achieve the said FDI could be performed by means of a GA approach. It must be noted that GAs are a class of evolutionary algorithms that take inspiration to the natural selection process. Optimization starts with a population of points (called chromosomes) which together represent the human genome. Each chromosome is a potential solution of the problem, the so called fitness function (i.e. the error function), calculated for each of them. According to the obtained value, a rank is assigned to them: since it is a minimization, chromosomes who give lower fitness values have a better rank and are selected to be the parents of a new population of points (the following generation) created by means of different operators called crossover (a combination of parents), migration and mutation. This process, widely described in [16], is repeated iteratively until the last child of the last generation fulfills a stopping criterion, that can be a tolerance on the fitness function, a limit on the stall generations, a maximum number of generations, etc. By tuning these settings, the method can be more or less fast or may or not converge to a final solution. It is important to consider that there is a strong dependence on the particular problem taken into account. GAs are generally suitable for parameters estimation since both single and multiple faults give accurate results for different levels of damage; furthermore, they are able to manage several parameters and, by making use of appropriate numerical devices (e.g. by parallelizing the calculation on different processors, adoption of appropriately simplified numerical models, implementation of the whole algorithm on low-level codes), it is possible to considerably reduce the calculation times making them compatible with the common maintenance procedures. However, since GAs can suffer from local minimum problems (i.e. they are not always able to identify the corresponding global minima), it is necessary to properly design and calibrate the algorithm [24].

Simulated Annealing

With respect to GAs, SA methods are more effective at finding the global minima, but at the cost of a larger amount of iterations [2, 25]. The SA method originates, as the name suggests, from the study of thermal properties of solids. Indeed, this procedure [17-18], was then an exact copy of the physical process which could be used to simulate a collection of atoms in thermodynamic equilibrium at a given temperature.

As reported in the literature [19-20], there is a significant correlation between the terminology of the thermodynamic annealing process (the behavior of systems with many degrees of freedom in thermal equilibrium at a finite temperature) and combinatorial optimization finding the global minimum of a given function based on many parameters.

TABLE 1. Association between thermodynamic simulation and combinatorial optimization

Thermodynamic Annealing	Combinatorial Optimization
System Stat	Feasible Solutions
Energy of a State	Cost of Solution
Change of state	Neighbor solution
Temperature	Control parameter
Minimum Energy	Minimum Cost

As shown in [26]. the aforesaid association between the thermodynamic simulation and the combinatorial optimization reported in Table 1 can be more clearly explained by noting that the cost of a solution represents the corresponding objective function value (i.e. the function that the optimization algorithm attempts to minimize in order to identify the optimal solution), the neighbor solution is a new system solution calculated by the optimization algorithm and evaluate, with respect to the previous one, using the said cost functions, and the control parameter is the system parameter iteratively modified by the optimization process so as to minimize its objective function, as shown in literature by [27-28]. Figure 2 shows the operating logic of the Simulated Annealing optimization method.

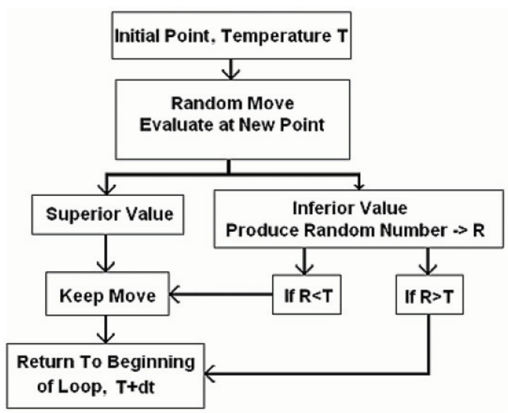


FIGURE 2. Operating Logic of Simulated Annealing Method [29-30].

CONCLUSIONS

In this work the author considered three Model-Based Fault Identification Methods applied to physical dynamic systems, introducing briefly their main characteristics, strengths, shortcomings and providing some bibliographic reference useful to understand these approaches or evaluate their performances.

As previously reported, the Failure Maps (FMs) method is relatively simple, not expensive for the processor and fast enough (reduced CPU time), but requires a rather complex and expensive preparation phase for identifying the aforesaid maps; however, being based on a deterministic type algorithm, this method is exempt from the criticalities typical of heuristic methods. Operatively speaking, it must be noted that the so obtained FDIs result typically rather coarse (as a consequence of the discretization introduced parametrizing the FMs curves), are able to handle only a few parameters (generally no more than two or three progressive failures) and their performances are markedly dependent on the uncertainties and errors that characterize the mapping process.

Vice versa, the Simulated Annealing (SA) results trustworthy also for combined failures and it is possible to assess its validity even on other possible different conditions (i.e. different combinations of progressive faults and boundary conditions).

With respect to other optimization algorithms that are highly dependent on good initial settings, SA-based algorithms are usually able to perform the optimization process reaching the corresponding global minimum independently by the starting settings. However, especially when it is necessary to manage an optimization process on many parameters, the SA shows its limits with respect to genetic algorithms, resulting less fast and effective

As regards genetic algorithms, they are usually effective and reliable in the FDI of failures precursors; in particular, GAs are particularly suitable for parameters estimation since both single and multiple faults give accurate results for different levels of damage. Compared to FMs and SA methods, GAs are certainly more performing and promising for FDI applications but, as already explained in the previous paragraph, it is necessary to appropriately design the algorithm to avoid (or, at least, appropriately limit) the risk of false positive and incorrect or omitted identifications. In conclusion, it should be noted that, although referred to an onboard application, the author already tested the three methods (FM, GA and SA) by means of a numerical test-bench simulating a typical electromechanical actuator for primary flight controls; several progressive failures have been evaluated and, as reported in [8, 11, 16, 31], the three FDI methods (albeit with different performances, calculation times and levels of accuracy) provided encouraging results.

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