Prognostics and Health Management of Industrial Equipment

Enrico Zio

Prognostics and Health Management of Industrial Equipment

E. Zio
Chair on Systems Science and the Energetic Challenge, European Foundation for New Energy-Electricite' de France, at Ecole Centrale Paris - Supelec, France
enrico.zio@ecp.fr, enrico.zio@supelec.fr

Politecnico di Milano, Italy
enrico.zio@polimi.it

ABSTRACT

Prognostics and health management (PHM) is a field of research and application which aims at making use of past, present and future information on the environmental, operational and usage conditions of an equipment in order to detect its degradation, diagnose its faults, predict and proactively manage its failures. The present paper reviews the state of knowledge on the methods for PHM, placing these in context with the different information and data which may be available for performing the task and identifying the current challenges and open issues which must be addressed for achieving reliable deployment in practice. The focus is predominantly on the prognostic part of PHM, which addresses the prediction of equipment failure occurrence and associated residual useful life (RUL).

INTRODUCTION

In human health care, a medical analysis is made, based on the measurements of some parameters related to health conditions; the examination of the collected measurements aims at detecting anomalies, diagnosing illnesses and predicting their evolution. By analogy, technical procedures of health management are used to capture the functional state of industrial equipment from historical recordings of measurable parameters (Vachtsevanos, Lewis, Roemer, Hess & Wu, 2006). With the term 'equipment', from now on we shall intend a System, Structure or Component (SSC).
The knowledge of the state of equipment and the prediction of its future evolution are at the basis of condition-based maintenance strategies (Jarrell, Sisk & Bond, 2004): according to these strategies, maintenance actions are carried out when a measurable equipment condition shows the need for corrective repair or preventive replacement. From the point of view of production performance, by identifying the problems in the equipment at their early stages of development, it is possible to allow the equipment to run as long as it is healthy and to opportunely schedule the maintenance interventions for the most convenient and inexpensive times. The driving objectives are maximum availability, minimum unscheduled shutdowns of production, economic maintenance (Jardine, Lin & Banjevic, 2006).
The condition of the equipment is usually monitored at a regular interval and once the reading of the monitored signal exceeds a threshold level, a warning is triggered and maintenance actions may be planned based on the prediction of the future evolution of the degradation process. The monitoring interval influences the equipment overall cost and performance: a shorter interval may increase the cost of monitoring, whereas a longer one increases the risk of failure. The monitoring system should be reliable in order to avoid false alarms. A decision must be taken every time an alarm is indicated; to ignore an alarm may give rise to serious consequences. A first option is to make further investigation of the alarm,

without stopping the equipment; an alternative option is to stop the equipment for an overhaul. In the first option, a false alarm would result in extra cost due to the time and manpower necessary to make the diagnosis; the second option could result in greater losses, where lost production and manpower costs occur simultaneously. The greatest losses will occur when ignoring the alarm, in case of accidents with damages and loss of assets.

The dynamic scheduling of condition-based maintenance represents a challenging task, which requires the prediction of the evolution of the monitored variables representing the equipment condition. Upon detection of failure precursors, prognostics becomes a fundamental task; this entails predicting the reliability or the probability of failure of the equipment at future times, and the residual useful life (RUL), i.e. the amount of time the equipment will continue to perform its function according to design specifications. This prediction/forecasting/extrapolation process needs to account for the current state assessment and the expected future operational conditions. The 'fortune teller' of such prognostic task is the intelligent integration of the information and data available into accurate models solved by efficient computational algorithms.

Equipment state knowledge and prediction are also central to the management of abnormal events in process plants (Venkatasubramanian, Rengaswamy, Yin & Kavuri, 2003). A single abnormal event may give rise to a catastrophic accident with significant economic, safety and environmental impacts (the accident at the Kuwait petrochemical refinery in 2000 led to an estimated 100 million dollars in damages (Venkatasubramanian et al.)). On the other hand, minor accidents occur relatively frequently and may cumulate to numerous occupational injuries and illnesses, and relevant costs to the industry (estimates of these costs in the US and UK range in the order of 20 billion dollars per year (Nimmo, 1995; Laser, 2000)). This explains the great interest in, and attention paid to the development of effective methods and procedures for abnormal event management.

Successful abnormal event management requires the timely detection of the abnormal conditions, diagnosis of the causal fault, prognosis of the process evolution; these elements feed the procedure of correction of the equipment fault and of plant control to safe conditions. From the point of view of safety, the recognition of the state of equipment (diagnostics) and prediction of its future evolution (prognostics) enable safer and more reliable operation, under a proactive approach to operations and maintenance which has the potential to improve the understanding of the (safety) margins between operating values and safety thresholds, prioritize aging factors that impact life cycle asset management in the long term, reduce unplanned outages, optimize staff utilization, reduce impacts to high value capital assets. These issues are of utmost relevance for the development and operation of technologies of safety concern, such as nuclear and process technologies.

Complete reliance on human operators for the management of abnormal events and emergencies has become increasingly difficult. In particular, the diagnostic and prognostic tasks in a complex plant are made quite difficult by the variety of equipment failure occurrences and of the related process responses, and by the large number of monitored process variables (of the order of a thousand in modern process plants) which lead to information overload. So, the grand challenge is the creation of adequate, automated methods for PHM of industrial equipment, in support to the human operators.

In the present paper, the focus is on prognostics. Due to the broad nature of the problem, it is not possible to be complete and exhaustive in its treatment and in the detailed discussion of the methods, nor in the reference to the specialized literature. The intent is to provide a general view on the state of knowledge and available methods of prognostics, placed in context with the types of information and data which may be available, while pointing at the main challenges and open issues for practical applications.

Indeed, the development of prognostic systems may rely on quite different information and data on the past, present and future behavior of the equipment; there may be situations in which sufficient and relevant statistical equipment failure data are available, others in which the equipment behavior is known in a sufficiently accurate way to allow building a sufficiently accurate model, and yet others with scarce data on the failure behavior of the equipment (this is typically the case of highly valued equipment which is rarely allowed to run to failure) but with available process data measured by sensors and related to the equipment degradation and failure processes. Correspondingly, a wide range of approaches have been developed, based on different sources of information and data, modeling and computational schemes, and data processing algorithms. A number of taxonomies have been proposed to categorize the different approaches (Pecht, 2008).

In general, a distinction can be made among first-principle model-based, reliability model-based and process sensor data-driven approaches (also referred to as white box, black box and grey box models, respectively). In the first type of approach, a mathematical model is derived from first principles to describe the degradation process leading to failure; the model is then used to predict the evolution of the equipment state and infer the (failure) time in correspondence of which the state reaches values beyond the threshold which describes loss of functionality. Where applicable, this approach leads to the most accurate prognostic results. The difficulty in its use lies in the definition of the model, which may turn out actually impossible for real complex systems subject to multiple, complicated, stochastic processes of degradation. Physic-based Markov models are a typical example. If experimental or field degradation data are available, they can be used to calibrate the parameters of the model or to provide ancillary information related to the degradation state, within the state-observer formulation typical of a filtering problem, e.g. Kalman and particle filtering (Myotyri, Pulkkinen & Simola, 2006; Pedregal & Carnero, 2006; Peel, 2008). Reliability model-based approaches use traditional reliability laws to estimate the RUL. They estimate the life of average equipment under average usage conditions. The parameters of the reliability models can be estimated on the basis of the available data related to the equipment failure behavior. In other words, time to failure data are used to tune the parameters of the failure time distribution. The most common way is by Weibull Analysis. It is also possible to include the effects of the environmental stresses (e.g. temperature, pressure, load, vibration, etc.) under which the equipment operates, to estimate the RUL of an average equipment under the given usage conditions. This can be done for example by the Proportional Hazard Models. Unfortunately, often in practice the availability of sufficiently representative data is rare, especially for very reliable equipment and for new equipment for which experience feedback data is scarce or non-existent. Finally, there are approaches which do not use any explicit model and rely exclusively on process data measured by sensors related to the degradation and failure states of the equipment. Empirical techniques like artificial neural networks, support vector machines, local Gaussian regression, pattern similarity are typical examples. The advantage of these methods lies on the direct use of the measured process data for equipment failure prognostics.

CHARACTERISTICS OF PROGNOSTICS METHODS

Some desirable characteristics of prognostic methods for practical application are listed below. Their degree of desirability is dependent on the type of equipment and on the objective of the PHM, also in view of its different benefits for production and safety as discussed in the previous Section.

Quick prediction

In the application of prognostics, the estimation of the equipment state and the prediction of its future evolution must be performed in a time which is compatible with the time scale of the equipment life and the time constants of the corrective actions (inspections, repairs, overhauls). If the prediction of failure is predicted ‘too early’, more than needed lead time is used to verify the developing failure, monitor the related variables and perform the preventive correction; on the contrary, if the failure is predicted too late, the time available to assess the situation and act accordingly is reduced. An even worse situation occurs if the failure prediction arrives after the failure has already occurred. In this sense, a positive time bias (early prediction) is preferable to a negative one (late prediction), and boundaries must be set on the maximum allowable late and early times of prediction. However, the timing of the prediction must be balanced with the need of collecting representative information and data sufficient for providing accurate results. Further, in fast developing situations, e.g. of accident management, the prediction task entails the use of fast-running, approximate models; in these cases, also a proper balance between computational rapidity and precision of the results must be sought, in order to avoid arriving quickly at wrong decisions of intervention.

Robustness

It is desirable that the performance of the prognostic method does not degrade abruptly in the presence of noises, uncertainties and novelties of situations. For the latter, it is important that the novel malfunctions be promptly recognized and the method adapt to recognizing and handling them.

Confidence Estimation

State estimations and predictions must be accompanied by a measure of the associated error, accounting for the incomplete and imprecise information available on the process. This measure is fundamental for projecting the confidence on the predictions of the RUL and the related decisions on the actions to take on the equipment to effectively and reliably control its function.
The best representation of the uncertainty associated to the RUL predictions is the complete distribution. This is usually possible to obtain when an analytical model for the prediction of the RUL is available, which also improves the understanding of the degradation behavior. However, this is not always the case in practice.

Adaptability

Processes in general change in time, as do the functioning of equipment due to changes in external environments, structural changes, changes in the input, retrofitting etc. The prognostic method must be able to accommodate these changes and perform equally well in different working conditions. A distinction between stationary and transient conditions is also expected to be needed, as the correlations among the process variables may differ significantly in the two cases, and require different methods ('static' methods like Principal Component Analysis, Partial Least Squares or others for the stationary conditions, and simulation and trend analysis methods for the transient case) (Hussey, Lu & Bickford, 2009).

Clarity of Interpretation

PHM methods in general are seen as constituting a complementary aid for plant operators. In this view, the prognostic indications provided must be clearly interpretable to allow the operator to act accordingly, in full conscience of the situations and confidence in the decisions. Graphical tools of representation of the outcomes of the analysis, and the associated uncertainty, can provide an added value.

Modeling and Computational Burden

For timely prognostics and clarity of interpretation, the amount of modeling required, and the storage and computational burden associated must be properly gauged to the application.

Multiple Faults Handling

Estimating the equipment state and predicting its evolution is an additional challenge whose solution must be provided for practical interests. A particular challenge relates to the possibility of diagnosing multiple faults simultaneously. A codebook approach would lead to the enumeration of an exponential number of possible fault combinations and their symptoms (Kliger, Yemini, Yemini, Oshie & Stolfo, 1995). Also, a combination of multiple faults may produce symptoms that can be confused with single fault symptoms while the effect of several failure mechanisms may be much higher than the sum of effects of each individual mechanism.
In general, the problem is NP-hard[1] both logically and probabilistically (de Kleer & Williams, 1987; Pearl, 1988) and the more combinations are possible, the more powerful and informative set of

---

[1] NP-hard (non-deterministic polynomial-time hard), in computational complexity theory, is a class of problems that are, informally, "at least as hard as the hardest problems in NP". A problem *H* is NP-hard if

measurements we need for discriminating among the different occurrences and avoiding shielding effects, i.e. conditions for which the failures of certain components render impossible the retrieval of information on the state of other components. Possible effective approaches to multiple fault handling might be ones that handle the faults incrementally as they occur over time; otherwise, some kind of approximation on the fault combinations considered is necessary (Rish, Brodie & Ma, 2002; Steinder & Sethi, 2002).

INFORMATION AND DATA FOR PHM

Different forms of information and data may be available for the prognostic assessment of the trajectory to failure of an equipment undergoing degradation:

- Equipment inherent characteristics (material, physical, chemical, geometrical etc.); these may vary from one individual equipment to another of the same type; this variability is described probabilistically by a probability distribution function of the values of the characteristic parameters.
- Time To Failure (TTF) data of a population of identical or similar equipment, e.g. as recorded for maintenance management purposes.
- External parameters (environmental, operational etc.) which may vary with time during the equipment life. They are not directly related to the equipment degradation state but may influence its evolution. Some of these parameters may be directly observable and measured by sensors, others may not; for some there may be a priori knowledge of their behavior in time (e.g. because defining the operational settings of the equipment, like in the flight plan of an airplane), while the behavior of others may be uncertain (e.g. because depending on external environmental conditions, like those occurring in the actual flight of an airplane).
- Data related to the values of observable process parameters measured by sensors during the evolutions to failure of a population of identical or similar equipment. The observable process parameters are directly or indirectly related to the equipment degradation state. It can then be assumed that a time-dependent parameter indicating the degradation state is available, either because one among the observable parameters directly measurable or because constructed/inferred from them. A threshold on such parameter is established, indicating failure of the equipment which is considered unable to function when the degradation parameter exceeds such threshold. These parameters can be called "Internal parameters" because, as explained, they are different from the "External parameters" of the first bullet above since they are related to the degradation state (for analogy, in health care the heartbeat of a human is an internal parameter).

Each of these sources of information may be available alone or in combination with other sources. The data may come from the field operation of the equipment or from experimental tests undertaken in laboratory under controlled conditions.

APPROACHES TO PHM

As said in the previous Section, the development of a prognostic system may face quite different situations with regards to the information and data available on the past, present and future behavior of the equipment; there may be situations in which sufficient and relevant TTF data on the equipment behavior are available, others in which the equipment behavior is known in a way to allow building a

---

and only if there is an NP-complete problem L that is polynomial time Turing-reducible to H (i.e., $L \le_T H$). In other words, *L* can be solved in polynomial time by an oracle machine with an oracle for *H*. Intuitively, we can think of an algorithm that can call such an oracle machine as a subroutine for solving *H*, and solves *L* in polynomial time, if the subroutine call takes only one step to compute. (Taken from http://en.wikipedia.org/wiki/NP-hard).

sufficiently accurate model, and yet others with scarce TTF data of the equipment, e.g. because being highly valued it is rarely allowed to run to failure, but with process data measured by sensors and related to the equipment degradation and failure processes. Correspondingly, a wide range of approaches have been developed, based on different sources of information, modeling schemes and data processing algorithms.

Various categorizations of these approaches have been proposed in the literature. Perhaps the most useful ones attempt to distinguish the approaches depending on the type of information and data they use, as discussed above. Still, in practice one is often faced with various sources of information and data on the equipment degradation and failure processes, which are best exploited in frameworks of integration of different types of prognostics approaches.

For the sake of presentation, here we distinguish among first-principle model-based, reliability model-based and process sensor data-driven approaches.

First-Principle Model-Based Approaches

In these approaches, mathematical models of the degradation process leading to failure are built and used to predict the evolution of the equipment state in the future, and infer its probability of failure and time to failure (Pecht, 2007).

The model is typically a system of equations which mathematically describe the evolution of the degradation, as known from first-principle laws of physics. Typical examples are the mathematical models describing the physical laws of evolution of cracks due to fatigue phenomena, of wearing and corrosion processes, etc. Experimental or field degradation data are used to calibrate the parameters of the model, which is then used to predict the degradation state evolution.

Most prognostic models of this type (e.g. Samanta, Vesely. Hsu & Subudly (1991), Lam & Yeh (1994), Hontelez, Burger & Wijnmalen (1996), Kopnov (1999), Bigerelle & Iost (1999), Berenguer, Grall & Castanier (2000)) track the degradation (damage) of the equipment in time and predict when it will exceed a predefined threshold of failure. Physics-based Markov models are often used to describe the degradation evolution in time (Kozin & Bogdanoff, 1989). In practice, the degradation measure may not be a directly measured parameter but it could be a function of several measured variables. If the actual equipment degradation state is not directly observable, then a state-observer formulation of the prognostic problem can be adopted in which a Markov state equation is used to represent the evolution of the hidden degradation state and an observation equation is introduced to relate the measured variables to the degradation state. This formulation sets up a typical framework of signal analysis by filtering approaches like Kalman filtering and particle filtering. Shock models can be introduced to describe the evolution of equipment subject to randomly arriving shocks which deliver a random amount of damage.

Reliability Model-Based Approaches

A common approach to prognostics of equipment failure time is by modeling its probability distribution, based on available TTF data from laboratory testing and field operation. The distribution thereby obtained allows estimating the lifetime of the average equipment under average usage conditions. A comprehensive review of these methods is found in (Si et al 2010).

The parametric distribution type most commonly used for prognostic purposes is the Weibull distribution which in terms of the formula for the hazard rate $\lambda(t)$ reads (Abernethy, 1996):

$$\lambda(t) = \frac{\beta}{\vartheta}\left(\frac{t}{\vartheta}\right)^{\beta-1} \tag{1}$$

With a proper choice of the value of the shape parameter β greater than unity, the hazard rate $\lambda(t)$ can model aging equipment, characterized by failure rates increasing in time.

A disadvantage of this approach is that it only provides the failure time distribution of the average equipment under average conditions of operations. On the contrary, it is expected that equipment under harsh conditions will fail at earlier times than equipment operating in mild environments. To account for the environment and operating conditions, stress data must be brought into the model. This leads to the development of degradation models including explanatory variables (covariates) that describe the operation environment. For example, the Proportional Hazard Model (PHM) is a method capable of including information on the environmental and operating conditions to modify a baseline, "average" hazard rate $\lambda_0(t)$ (Cox, 1972; Cox & Oakes, 1984; Bendell, Wightman & Walker, 2002):

$$\lambda(t;z) = \lambda_0(t)\exp\left(\sum_{j=1}^{q} \beta_j z_j\right) \tag{2}$$

The environmental information condition is represented by the multiplicative covariates z_j and failure data collected at different covariate conditions are used to estimate the coefficients β_j by ordinary least square algorithms (Vlok, Coetzee, Banjevic, Jardine & Makis, 2002). Time-dependent covariates can also be included, within a gamma process description of the increasing degradation (Bagdonavicius & Nikulin, 2000; Deloux, Castanier & Berenguer, 2008).
An alternative approach is that of the cumulative hazard rate, which also amounts to modeling the effect of the environment by the introduction of covariates in the hazard function (Singpurwalla, 1995; Singpurwalla, 2006).
Markov models can also be used to account for the influence of the working environment on the equipment failure behavior (Samanta et al., 1991; Yeh, 1997; Grall, Berenguer & Chu, 1998; Marseguerra, Zio & Podofillini, 2002; Zhao, Fouladirad, Berenguer & Bordes, 2008). This typically entails:

- The definition of a prognostic parameter which indicates the equipment failure condition state, upon comparison with a threshold. The value of the prognostic parameter for which actual equipment failure occurs is typically uncertain and can be established via statistical analysis of failure data, if available.
- The development of a stochastic model of the random evolution of the environmental conditions, based on the physics of the process.
- The development of a stochastic functional relationship of the effect of the environmental conditions on the evolution of the prognostic parameter. Usually, the functional form of this relationship is cumulative, since the environmental stressors tend to non-decreasingly deteriorate the equipment.

A disadvantage is the large number of degradation states and related probability distribution parameters to be fitted by data (Zille, Despujols, Bataldi, Rossetti & Zio, 2009). Indeed in practice, reliability model-based approaches suffer from the fact that equipment becomes more and more reliable, so that fewer data are available for fitting the reliability model distributions (Coble & Hines, 2009a) and the estimation of the characteristic parameters is quite difficult even by accelerated life testing (Bagdonavicius & Nikulin, 2000; Lehmann, 2006). For this reason, alternative hybrid approaches, based on the integration of fuzzy logic models are investigated with the aim of including in the model also qualitative information on the operational and environmental conditions based on expert knowledge of the equipment design, usage, degradation processes and failure modes (Baraldi, Zio, Compare, Rossetti & Despujols, 2009).
General Path Models (GPM) are also used to predict future degradation in time, based on measurable degradation data collected. A functional relationship is established of the damage evolution in time and the model parameters are estimated using historical data (Lu & Meeker, 1993). The underlying model describes the equipment degradation in terms of the evolution of an identified prognostic indicator of damage; the model accounts for both population (fixed) and individual (random) effects. The adaptability of the predictive model to changing scenarios of working conditions can be achieved by a dynamic Bayesian approach for updating the parameters estimates as historical degradation data become available from tests or field operation (Coble & Hines, 2009a)0.

Process Sensor Data-Driven Approaches

In situations where developing physics-based models of the degradation and failure behavior of an equipment is not possible or favorable, sufficient TTF data are not available whereas process sensors are available, which collect data related to the degradation state of the equipment, one can employ a data-driven approach to prognostics (Schwabacher, 2005; Hines, Garvey, Preston & Usynin, 2008). In this case, the prognosis of the state of the equipment for RUL estimation relies on the availability of run-to-failure data. Based on these data, the RUL can be estimated either directly through a multivariate pattern matching process from the data to the remaining life, or indirectly through damage estimation followed by extrapolation to damage progression up to the failure threshold. The latter approach is closer to the typical engineering reasoning but requires the definition of both the damage parameter and the failure criterion.

Common to all data-driven approaches is the estimation of the output values, without necessarily modeling the equipment physical behavior and operation. Such approaches include conventional numerical algorithms like linear regression and time series analysis (Hines & Garvey, 2007) as well as machine learning and data mining algorithms, like artificial neural networks, fuzzy logic systems, support vector machines (Vachtsevanos & Wang, 2001; Wang, Yu & Lee, 2002; Wang, Goldnaraghi & Ismail, 2004; Yan, Koç & Lee, 2004; Schwabacher & Goebel, 2007; Sotiris & Pecht, 2007; Peng, Zhang & Pan, 2010; Sikorska, Kelly & McGrath, 2010; Heng et al., 2009). Indeed, since predicting the TTF of an equipment can be seen as a regression problem, regression analysis and time-series estimation and forecasting methods can be used to build models for the direct estimation of the TTF from the available data.

EXAMPLES

For exemplary purposes, one first-principle model-based approach, within a filtering framework, and one data-driven approach are here illustrated with reference to their application in a prognostic task regarding a non linear fatigue crack growth process, typical of a certain class of industrial and structural equipment (Oswald & Schueller, 1984; Sobezyk & Spencer, 1992; Bolotin & Shipkov, 1998; Myotyri et al., 2006). The choice of the approaches presented is not motivated by any declaration of alleged superiority in comparison to the many other methods proposed in the literature, but by the need to rely on the experience of the author in their development and application.

The common Paris-Erdogan model is adopted for describing the evolution of the crack depth x as a function of the load cycles t (Pulkkinen, 1991):

$$\frac{dx}{dt} = C(\Delta S)^m \qquad (3)$$

where C and m are constants related to the material properties (Provan, 1987; Kozin & Bogdanoff, 1989), which can be estimated from experimental data (Bigerelle & Iost, 1999) and ΔS is the stress intensity amplitude, roughly proportional to the square root of x (Provan, 1987):

$$\Delta S = \gamma\sqrt{x} \qquad (4)$$

where γ is again a constant which may be determined from experimental data.

The intrinsic stochasticity of the process may be inserted in the model by modifying equation (3) as follows (Provan, 1987):

$$\frac{dx}{dt} = e^{\omega} C\left(\gamma\sqrt{x}\right)^m \qquad (5)$$

where $\omega \sim N(0,\sigma_\omega^2)$ is a white Gaussian noise. For Δt sufficiently small, the state-space model (5) can be discretized to give:

$$x(t_k) = x(t_{k-1}) + e^{\omega_j} C(\Delta S)^m \Delta t \qquad (6)$$

which represents a non-linear Markov process with independent, non-stationary degradation increments of the degradation state x.

At the generic inspection time T_j, the degradation state $x(T_j)$ is generally not directly measurable. In the case of non-destructive ultrasonic inspections a logit model for the observation $f(T_j)$ can be introduced (Simola & Pulkkinen, 1998):

$$\ln \frac{f(T_j)}{d - f(T_j)} = \gamma_0 + \gamma_1 \ln \frac{x(T_j)}{d - x(T_j)} + \upsilon_k \qquad (7)$$

where d is the equipment material thickness, $\gamma_0 \in (-\infty, \infty)$ and $\gamma_1 > 0$ are parameters to be estimated from experimental data and υ is a white Gaussian noise such that $\upsilon \sim N(0, \sigma_\upsilon^2)$.

The following standard transformations are introduced:

$$y(T_j) = \ln \frac{f(T_j)}{d - f(T_j)} \qquad (8)$$

$$\mu(T_j) = \gamma_0 + \gamma_1 \ln \frac{x(T_j)}{d - x(T_j)} \qquad (9)$$

In the case study here considered (taken from Myotyri et al. (2006)), the parameters of the state equation (6) are $C = 0.005$, $m = 1.3$ and $\gamma = 1$, whereas those in the measurement equation (7) are $\gamma_0 = 0.06$, and $\gamma_1 = 1.25$. The process and measurement noise variances are $\sigma_\omega^2 = 2.89$ and $\sigma_\upsilon^2 = 0.22$, respectively.

The equipment is assumed failed when the crack depth $x \geq d = 100$, in arbitrary units.

Figure 1 shows the degradation-to-failure pattern that in the following will be used as test pattern in the procedure for predicting the equipment RUL. The crack depth x reaches the full material thickness d=100 at 802 [min].

Figure 1. Crack growth pattern used as test pattern

In the case study, the interval between two successive inspections is equal to 100 [min], if the estimated RUL>200 [min] or otherwise it is equal to 10 [min], reflecting a more frequent inspection of the equipment integrity as the equipment is approaching the end of life.

A First-Principle Model-Based Approach by Particle Filtering

In general terms, under a filtering formulation of the first-principle model-based approach the problem of estimating the degradation state of an equipment is carried out in a discrete time domain, considering both a set of measurements and a model linking the equipment states among themselves and with the measurements.

In correspondence of a sequence of equidistant discrete times t, where t stands for $\tau_t = t \cdot \Delta t, (t = 0,1,2,....)$, it is desired to infer the unknown (hidden) state $x_t \equiv x(\tau_t)$ on the basis of all the previously estimated state values $x_{0:t-1} \equiv (x_0, x_1, ..., x_{t-1})$ and of all the measurements $z_{0:t} \equiv (z_0, z_1, ..., z_t)$, $z_i \equiv z(\tau_i)$, collected up to time *t* by a set of sensors. Both the equipment states and the measurements, which may be multidimensional variables, are affected by inherent noises.

In a Bayesian context, the associated filtering problem amounts to evaluating the posterior distribution $p(x_t \mid z_{0:t})$. This can be done by sampling a large number N_s of time sequences $\{x_{0:t}^i\}_{i=1}^{N_s}$ from a suitably introduced importance function $q(x_{0:t} \mid z_{0:t})$ (Doucet, de Freitas & Gordon, 2001). In the state space, this sample of sequences represents an ensemble of trajectories of state evolution similar to those simulated in particle transport phenomena: the problem is then that of utilizing the ensemble of N_s simulated trajectories for filtering out the unobserved trajectory of the real process.

The filtering distribution $p(x_t \mid z_{0:t})$ is the marginal of the probability $p(x_{0:t} \mid z_{0:t})$, i.e. the multiple integral of this latter with respect to $x_{t_0}, x_{t_1}, \ldots, x_{t-1}$ in $[-\infty, \infty]^t$ viz., $p(x_t \mid z_{0:t}) = \int p(x_{0:t} \mid z_{0:t}) dx_{0:t-1}$. The integration may be formally extended to include also the variable xt by means of a δ-function, i.e. $p(x_t \mid z_{0:t}) = \int p(x_{0:t-1}, u \mid z_{0:t}) \delta(x_t - u) dx_{0:t-1} du$. By sampling a large number Ns of trajectories $\{x_{0:t}^i\}_{i=1}^{N_s}$ from the importance function $q(x_{0:t} \mid z_{0:t})$, the integral is approximated as

$$p(x_t \mid z_{0:t}) = \int \left[\frac{p(x_{0:t-1}, u \mid z_{0:t})}{q(x_{0:t-1}, u \mid z_{0:t})} \delta(x_t - u) \right] q(x_{0:t-1}, u \mid z_{0:t}) dx_{0:t-1} du \approx \sum_{i=1}^{N_s} w_t^i \delta(x_t - x_t^i) \tag{10}$$

where the weights w_t^i of the estimation are

$$w_t^i = \frac{p(x_{0:t}^i \mid z_{0:t})}{q(x_{0:t}^i \mid z_{0:t})} \tag{11}$$

which can be recursively computed as

$$w_t^i = w_{t-1}^i \frac{p(z_t \mid x_t^i) p(x_t^i \mid x_{t-1}^i)}{q(x_t^i \mid x_{t-1}^i)} \tag{12}$$

Unfortunately, the trajectories sampled according to the procedure illustrated suffer from the so called degeneracy phenomenon: after few samplings, most of the N_s weights in (12) become negligible so that the corresponding trajectories do not contribute to the estimate of the probability density function (pdf) of interest (Doucet et al., 2001):.

A possible remedy to this problem is to resort to the so called resampling method (Arulampalam, Maskell, Gordon & Clapp, 2002), based on the bootstrap technique which essentially consists in sampling balls from an urn with replacement (Efron, 1979; Efron & Tibshirani, 1993). At each time *t*, N_s samplings with replacement are effectuated from an urn containing N_s balls; the i-th ball is labelled with the pair of known numbers $\{w_t^i, x_t^i\}$ and it will be sampled with a probability proportional to the weight value w_t^i; a record of the sampled pairs is maintained; at the end of these *N* multinomial samplings, there is a good chance that the recorded sample will contain several replicas of the balls with larger weights (in other words, that the final record will contain several identical copies of the same label), whereas a corresponding number of balls with smaller weights will not appear in the sample (in other words, a corresponding number of labels is lost from the sample).

In the described bootstrap procedure, it is evident that the sampled weights are i.i.d. so that the same weight $1/N_s$ may be assigned to all sampled pairs. Then, the filtering procedure continues with the original pairs $\{w_t^i, x_t^i\}_{i=1}^{N_s}$ replaced by new pairs $\{1/N_s, x_t^{i^*}\}_{i^*=1}^{N_s}$ in which several i^* may correspond to the same i in the original pairs. Equation (10) then becomes

$$p(x_t \mid z_{0:t}) \approx \sum_{i=1}^{N_s} \frac{p(z_t \mid x_t^i) p(x_t^i \mid x_{t-1}^i)}{q(x_t^i \mid x_{t-1}^i)} \delta(x_t - x_t^i) \approx \sum_{i=1}^{N_s} \frac{1}{N_s} \delta(x_t - x_t^{i^*}) \tag{13}$$

A pseudo-code describing the basic steps of the procedure is:

- at t=0, a sequence $\{x_0^i\}_{i=1}^{N_s}$ is sampled from $p(x_0)$;
- at the generic time t>0:
  - a value z_t is measured (or simulated if we are dealing with a case study);
  - a sequence $\{x_t^i\}_{i=1}^{N_s}$ is sampled from the given $q(x \mid x_{t-1}^i)$;
  - the N_s likelihoods $\{p(z_t \mid x_t^i)\}_{i=1}^{N_s}$ are evaluated;
  - the weights w_t^i required by the described resampling procedure are evaluated from (12) in which $w_{t-1}^i = 1$;
  - the resampling procedure is performed and the obtained $x_t^{i^*}$ yield the resampled realizations of the states at time t;
  - the $x_t^{i^*}$ -range, $X_t = \max_{i^*}(x_t^{i^*}) - \min_{i^*}(x_t^{i^*})$, is divided in a given number of intervals and the mean probability values in these intervals are given by the histogram of the $x_t^{i^*}$.

The particle filtering estimation method has been applied to the case study of literature previously illustrated, concerning the nonlinear crack propagation due to fatigue as modelled by the Paris-Erdogan law.
The application of particle filtering for RUL estimation entails the evaluation of the conditional cumulative distribution function (cdf) of the stochastic observable variable related to the degradation state. For more details on the procedure, the interested reader may refer to Cadini, Zio & Avram (2009).
From Eq. (8) it follows that the transformed observation $Y(T_j) \sim N(\mu(T_j), \sigma_\upsilon^2)$ is a Gaussian random variable with cdf:

$$cdf_{Y(T_j)}\left(y(T_j) \middle| x(T_j)\right) = P\left(Y(T_j) < y(T_j) \middle| x(T_j)\right) = \Phi\left(\frac{y(T_j) - \mu(T_j)}{\sigma_\upsilon}\right) \tag{14}$$

where $\Phi(u)$ is the cdf of the standard normal distribution $N(0,1)$.
The conditional cdf of the stochastic measurement variable $F(T_j)$ related to the stochastic degradation state $X(T_j)$ is then:

$$cdf_{F(T_j)}\left(f(T_j) \middle| x(T_j)\right) = cdf_{Y(T_j)}\left(\ln \frac{f(T_j)}{d - f(T_j)} \middle| x(T_j)\right) = \Phi\left(\frac{1}{\sigma_\upsilon}\left(\ln \frac{f(T_j)}{d - f(T_j)} - \mu(T_j)\right)\right) \tag{15}$$

with corresponding pdf:

$$pdf_{F(T_j)}\left(f(T_j) \middle| x(T_j)\right) = \frac{1}{\sqrt{2\pi}\sigma_\upsilon} e^{-\frac{1}{2}\left(\frac{\ln \frac{f(T_j)}{d - f(T_j)} - \mu(T_j)}{\sigma_\upsilon}\right)^2} \frac{d}{f(T_j) \cdot \left(d - f(T_j)\right)} \tag{16}$$

The estimates of the RUL obtained resorting to particle filtering are plotted in Figure 2 in thin continuous lines with the bars of one standard deviation of the samples; the $R\hat{U}L(T_j)$ estimates at the inspection times of Figure 2, are indicated in squares. After fault detection, the particle filtering estimates $R\hat{U}L\left(T_j\right)$ are shown to move away from the Mean Time To Failure $MTTF\left(T_j\right)$ values towards the real RUL (dashed thick line). In the Figure, the bold vertical line indicates the time of crack depth exceedance of the limit on the material thickness.

Figure 2. Comparison of the RUL estimations for the crack propagation pattern of Figure 1 provided by the particle filtering and similarity-based approaches

A Data-Driven Approach: Pattern Fuzzy Similarity

In general terms, in a similarity-based approach to RUL estimation, it is assumed that J measurements taken at predefined inspection times are available for N degradation-to-failure trajectories (reference patterns) of equipment of the type of interest; these trajectories last all the way to equipment failure, i.e., to the instance when the degradation state reaches the threshold value beyond which the equipment loses its functionality (Dubois, Prade & Testemale, 1988; Joentgen, Mikenina, Weber & Zimmermann, 1999).
A degradation trajectory (test pattern) is developing in the equipment under analysis, which is monitored at the predefined inspection times. The RUL estimation for the degrading equipment is performed by analyzing the similarity between the test pattern and the N reference patterns, using their RULs weighted by how similar they are to the test pattern (Angstenberger, 2001; Wang, Yu, Siegel & Lee, 2008).
The ideas behind the weighting of the individual RULs are that: i) all reference patterns bring useful information for determining the RUL of the degradation pattern currently developing; ii) those segments of the reference patterns which are most similar to the most recent segment of length n of the currently developing degradation pattern should be more informative in the extrapolation of the occurring pattern to failure.
For more details on the procedure, the interested reader may refer to Zio & Di Maio (2010).
The procedure has been applied to the fatigue crack propagation case study. A database of $N = 50$ reference crack propagation patterns of differing initial conditions has been used. These are compared for similarity with the test pattern containing the values of the measured signal of the developing degradation pattern of Figure 1. The RUL estimates of the individual reference patterns are computed and then aggregated in a weighted sum, with the weights opportunely calculated (Zio & Di Maio, 2010).
The estimates of the $MTTF\left(T_j\right)$ are plotted in Figure 2 in circles linked by a thick continuous line with the bars of one standard deviation Again, the estimates $R\hat{U}L\left(T_j\right)$ at the beginning match the $MTTF\left(T_j\right)$; then, upon fault detection, the $R\hat{U}L\left(T_j\right)$ estimates move away from the $MTTF\left(T_j\right)$ values towards the real RUL value.

CHALLENGES AND WAYS FORWARD

PHM is the pinnacle of reliability engineering and abnormal event (accident) management for safety. The ability to confidently predict the probability of failure and the RUL of an equipment provides a valuable aid to the human operators who are to decide when to take maintenance actions or operational decisions, e.g. as to whether shut down or alter the operational configuration to steer the plant to a safe state.
However, a number of challenges and open issues remain in the field of PHM in general, and of prognostics in particular (Hines & Usynin, 2008). Some are listed and synthetically discussed below: their resolution has become a priority in high-valued technologies such as those of the nuclear and petrochemical industries, for current and future plants deployment and operation.

Hybrid Information and Data

The efficacy of a prognostic model relies on the information and data available. These often come from multiple sources (e.g. equipment parameters measured by multiple, different sensors) of different types (including measured equipment parameters values and time-to-failure data from maintenance records): their fusion into an effective prognostic algorithm represents a fascinating challenge (Goebel & Bonissone, 2005). The data must be integrated across different collection platforms, with all issues associated to different interfaces, resolutions and coverages (US Department of Energy, 2002).
Attempts in this direction are being made (Muller, Suhner & Iung, 2008). In Aumeier, Alpay, Lee & Akcasu (2006), a probabilistic dynamics framework which combines a Bayesian formulation with the solution of the Chapman-Kolomogorov equation has been developed for fault diagnosis. The generalized system transport equation which is formulated makes explicit use of the equipment reliability data, the process data and plant measurements, thus with the hybridization of the continuous process variables and discrete equipment states within a proper mathematical model of the transport of the system among its reachable states. The probability density functions of state transitions are then obtained via an adaptive Kalman filtering approach. The application of the method in practice and its extension to prognosis would be an attractive challenge, with significant potential. In Gebraeel, Elwany & Pan (2009), equipment failure times from historical maintenance records are first fitted to a Bernstein distribution by maximum likelihood estimation; the estimated parameters are used to estimate the prior distributions of the parameters of a linear or exponential degradation model; a bayesian approach is adopted to update the degradation model parameters, based on the real-time observation of the degradation signals evolution. Furthermore, even in cases where no failures have been explicitly documented or observed there may exist a way to exploit the data available on the equipment behavior for PHM purposes (Sotiris, Tse & Pecht, 2010).
In effects, a wide range of situations may be encountered in PHM, with respect to information and data availability. One may deal with equipment time-to-failure data only, with the current historical pattern of degradation developing in the equipment, with the historical patterns of degradation of similar equipments under similar operating conditions, with information on exogenous operational and environmental parameters, with any combination of these: depending on the situation, different methods, or their combination thereof, may be applied with more or less success. A structured procedure for guiding the choice of the approach to follow in the different situations is needed.

Definition of Prognostic Indicators

The efficacy of a prognostic method relies on the representativeness of the prognostic indicators chosen. A number of desirable characteristics are expected to be look at in the choice (Vachtsevanos, 2003; Coble & Hines, 2009a):

- Monotonicity: The indicators are wished to present an overall positive or negative trend in time, excluding possible self-healing situations.
- Prognosability: The distribution of the final value that an indicator takes at failure is wished to be 'peaked', i.e. not too wide-spread.
- Trendability: The entire histories of evolution of the indicator towards failure are wished to have quite similar underlying shapes, describable with a common underlying functional form.

Other characteristics may be desirable. For any characteristic sought, a metric must be introduced to allow comparing the different potential prognostic indicators on the different characteristics. A detailed list of possible metrics, and their meaning, is given in Saxena et al. (2008) with the distinction among accuracy-based, precision-based and robustness-based metrics. Furthermore, in the manipulation of prognostic indicators for the tasks of state estimation and prediction it is often convenient to reduce the multivariate problem into a single-variable one, by opportunely combining the multiple indicators, e.g. by weighted average (Coble & Hines, 2009b). Multiobjective optimization problems may arise from these issues.

Ensemble and Hybrid Methods

Increasing interest is arising towards the use of ensembles of diagnostic and prognostic models for PHM. These ensembles build their state estimation and prediction from a combination of the estimates and predictions of a set of individual models. The individual models perform well and make errors in different regions of the parameters space; the errors are balanced out in the combination and as a result the performance of the ensemble is superior to that of the single best model of the ensemble (Polikar, 2006; Baraldi, Razavi-Far & Zio, 2011). Furthermore, by exploiting the nature of the ensemble itself, it is possible to provide measures of confidence in the ensemble outcomes (Baraldi, Razavi-Far & Zio, 2010). More so, given the variety of information and data sources and types, and of prognostic indicators and their characteristics, it is becoming more and more attractive to ensemble-combine first-principle model-based and process sensor data-driven PHM methods (Penha & Hines, 2002; Peel, 2008; Yan & Lee, 2008). This way of proceeding is aimed at augmenting the robustness and interpretability of first-principle model-based methods with the sensitivity of process sensor data-driven methods. The modeling framework underpinning hybrid methods is certainly more complicated, but offers clear advantages on the reliability of the predictions. Purely process sensor data-driven methods cannot guarantee effective performance in their extrapolation to new regions of operation determined by plant configuration changes and/or external factors: steering the predictions towards the first-principle model-based ones when new operating conditions are encountered, and to process sensor data-driven ones when in the familiar operating conditions allows to improve the reliability of the prognosis; the investigation on efficient methods of steering hybrid methods need to be continued.

RUL and Reliability Estimation with Uncertainty Quantification

A prognostic method should provide the estimation of the equipment RUL as well as of its reliability, with the related uncertainties. The proper assessment of the uncertainties in the prognostic outcomes is fundamental for their effective and reliable use. Uncertainty in inputs, model parameters and structure, algorithms, operational modes must all be properly represented and propagated. Efforts are being made in this direction, both for first-principle and reliability model-based (Orchard, Kacprzynski, Goebel, Saha & Vachtsevanos, 2008), as well as for process sensor data-driven methods (Chryssolouris, Lee & Ramsey, 1996; Zio, 2006).

Validation and Verification of Prognostic Methods

At the level of research and development, it seems desirable that benchmarks on common datasets and with agreed evaluation criteria be established, to allow the evaluation of the technical and economical feasibility of the different prognostic methods proposed. From the practical application point of view, proof-of concept experiments and proof-of-practice applications are needed in order to be able to license a prognostic method with given measures of accuracy, stability and reliability (Byington, Roemer & Kalgren, 2005; Dzakovic & Valentine, 2007). In the case of high-value equipment (e.g. those employed in the nuclear, aerospace and process industries), this poses the problem of dimensional scaling and accelerated testing of integral testing facilities (Coble & Hines, 2009b).

Instrumentation Design

Although not in the scope of the present paper, it seems in order to also mention the fundamental role played by the instrumentation for data measurement. The possibility of efficiently collecting and managing field data on equipment degradation and failure processes is the cornerstone which PHM is founded upon. The design of the required instrumentation must then be planned harmoniously with the planning of the PHM methods, so as to avoid the difficult, cumbersome and less efficient work of retrofitting the instruments to the methods or vice versa. Also, datasets should be shared among the researchers in the field, so as to allow consistent evaluation of the different methods proposed.

PHM Integration in Control, Operation and Maintenance Procedures

The final challenge for practical application of PHM is its integration within the autonomous, intelligent plant control and information systems which are nowadays deployed on one side, and with the inspection and testing procedures which support preventive (on condition) maintenance on the other side. This will provide a complete and valuable decision-making asset for the operators during abnormal events and emergency accidents.

SUMMARY AND CONCLUSIONS

PHM is destined to play a more and more relevant role in modern maintenance practice and accident management, supported by the maturity of condition monitoring technology. The promises of reducing downtime, spares inventory, maintenance costs and risk exposure are very attractive for the Industry. However, to date most prognostic studies have been carried out in research laboratories, where simplifications of certain practical aspects are often adopted.

This paper has reviewed the state of knowledge on the different methods for performing PHM, placing them in context with the different information and data which may be available for capturing and predicting the health state of industrial equipment. The practical requisites of PHM methods have been laid out and the types of data and information upon which these methods may rely have been specified. This has guided the illustration of the different approaches for PHM, under a classification into first-principle model-based, reliability model-based and process sensor data-driven. Examples have been given with reference to the prognostics of a non linear fatigue crack growth process typical of a certain class of industrial and structural equipment. In particular, particle filtering and pattern fuzzy similarity have been illustrated and compared with respect to their strengths and similarities. Finally, a discussion has been provided on the main challenges and open issues of PHM in general, and of prognostics in particular, with the hope of stimulating researchers to contributing the developments necessary for its full maturity and application. The ultimate goal indeed remains to be achieved, that of developing reliable prognostic frameworks for application to real-life situations.

REFERENCES

Abernethy, R.B. (1996). *The New Weibull Handbook*, 2nd edition, ISBN 0 9653062. North Palm Beach, pa: Robert B. Abernethy.

Angstenberger, L. (2001). Dynamic fuzzy pattern recognition. In H.J. Zimmermann (Ed.)*, International series in intelligent technologies, 17*. Dordrecht, PA: Kluwer Academic Publishers.

Arulampalam, M.S., Maskell, S., Gordon, N., & Clapp, T. (2002). A Tutorial on Particle Filters for Online Nonlinear/Non-Gaussian Bayesian Tracking. *IEEE Transactions on Signal Processing, 50(2),* 174-188.

Aumeier, S.E., Alpay, B., Lee, J.C., & Akcasu, A.Z. (2006). Probabilistic Techniques for Diagnosis of Multiple Component Degradations. *Nuclear Science and Engineering, 153*, 101-123.

Bagdonavicius, V., & Nikulin, M. (2000). Estimation in Degradation Models with Explanatory Variables. *Lifetime Data Analysis, 7*, 85-103.

Baraldi, P., Razavi-Far, R., & Zio, E. (2010, November). *A Method for Estimating the Confidence in the Identification of Nuclear Transients by a Bagged Ensemble of FCM Classifiers*. Paper presented at the 7th American Nuclear Society International Topical Meeting on Nuclear Plant Instrumentation, Controls and Human Machine Interface Technology, Las Vegas, Nevada, USA.

Baraldi, P., Razavi-Far, R., & Zio, E. (2011). Bagged Ensemble of FCM Classifier for Nuclear Transient Identification. *Annals of Nuclear Energy, 38(5)*, 1161-1171.

Baraldi, P., Zio, E., Compare, M., Rossetti, G., & Despujols, A. (2009, September). *A Novel approach to Model the Degradation of components in electrical production plants*. Paper presented at the European Safety and Reliability Conference, Prague, Czech Republic.

Bendell, D., Wightman and, D., & Walker, E. (1991). Applying Proportional Hazard Modeling in Reliability. *Reliability Engineering and System Safety, 34*, 35-53.

Bérenguer, C., Grall, A., & Castanier, B. (2000). *Simulation and evaluation of condition-based maintenance policies for multi-component continuous-state deteriorating systems* (pp.275-82). In: Cottam M, Harvey D, Pape R, Tait J, (Eds). Proceedings of the ESREL 2000 Foresight and Precaution conference.). Rotterdam, Netherlands: Balkema Publishers.

Bigerelle, M., & Iost, A. (1999). Bootstrap Analysis of FCGR, Application to the Paris Relationship and to Lifetime Prediction. *International Journal of Fatigue, 21*, 299-307.

Bolotin, V.V., & Shipkov, A.A. (1998). A model of the environmentally affected growth of fatigue cracks. *Journal of Applied Mathematics and Mechanics, 62*, 313.

Byington, C.S., Roemer, M.J., & Kalgren, P.W. (2005, April). *Verification and Validation of Diagnostic/Prognostic Algorithms*. Paper presented at Machinery Fault Prevention Technology Conference (MFPT 59). Virginia Beach, Virginia, USA.

Cadini, F., Zio, E., & Avram, D. (2009). Monte Carlo-based filtering for fatigue crack growth estimation: *Probabilistic Engineering Mechanics 24*, 367-373.

Chryssolouris, G., Lee, M., & Ramsey, A. (1996). Confidence Interval Prediction for Neural Network Models. *IEEE Transactions on Neural Networks, 7(1)*, 229-232.

Coble, J., & Hines, J.W. (2009a, April). *Fusing Data Sources for Optimal Prognostic Parameter Selection*. Paper presented at the 6th American Nuclear Society International Topical Meeting on Nuclear Plant Instrumentation, Controls and Human Machine Interface Technology, Knoxville, TN, US.

Coble, J., & Hines, J.W. (2009b, April). *Analysis of Prognostic Opportunities in Power Industry with Demonstration*. Paper presented at the 6th American Nuclear Society International Topical Meeting on Nuclear Plant Instrumentation, Controls and Human Machine Interface Technology, Knoxville, Tennessee, USA.

Cox, D. (1972). Regression Models and Life Tables. *Journal of the Royal Statistics B, 34*,187-202.

Cox, D.R., & Oakes, D. (1984). *Analysis of Survival Data*. USA: Chapman and Hall.

de Kleer, J., & Williams, B.C. (1987). Diagnosing Multiple Faults. *Artificial Intelligence*, *32(1)*, 97-130.

Deloux, E., Castanier, B., & Bérenguer C. (2008, September). *Condition-based maintenance approaches for deteriorating system influenced by environmental conditions*. Paper presented at the European Safety and Reliability Conference. Valencia, Spain.

Doucet, A., de Freitas, J.F.G., & Gordon, N.J. (2001) An Introduction to Sequential Monte Carlo Methods. In A. Doucet, J.F.G. de Freitas and N.J. Gordon (Eds.), *Sequential Monte Carlo in Practice*. New York: Springer-Verlag.

Dubois, D., Prade, H., & Testemale, C. (1988). Weighted Fuzzy Pattern Matching. *Fuzzy Sets and Systems, 28*, 313-331.

Dzakowic, J.E., & Valentine, G.S. (2007, April). *Advanced Techniques for the Verification and Validation of Prognostics and Health Management Capabilities.* Paper presented at Machinery Failure Prevention Technology (MFPT 60). Virginia Beach, Virginia, USA.

Efron, B. (1979). Bootstrap Methods: Another Look at the Jacknife. *Annals of Statistics, 7*, 1-26.

Efron, B., & Tibshirani, R.J. (1993). *An Introduction to the Bootstrap*. New York, PA: Chapman and Hall.

Gebraeel, N., Elwany, A., & Pan, J. (2009). Residual Life Predictions in the Absence of Prior Degradation Knowledge: *IEEE Transactions on Reliability, 58(1)*, 106-117.

Goebel, K., & Bonissone, P. (2005). Prognostic Information fusion for Constant Load Systems. In *Proceedings of the 7th Annual Conference on Information Fusion, 2* (pp. 1247-1255).

Grall, A., Bérenguer, C., & Chu, C. (1998). Optimal dynamic inspection/replacement planning in condition-based maintenance. In: S. Lydersen, G. Hansen, H. Sandtorv (Eds.), *Proceedings of the*

European safety and reliability conference ESREL'98 (pp. 381-388). Rotterdam, Netherlands: Balkema Publishers.

Heng, A., Tan, A., Mathew, J., Montgomery, N., Banjevic, D., & Jardine, A. (2009). Intelligent condition-based prediction of machinery reliability. *Mechanical Systems & Signal Processing*, *23(5)*, 1600-1614.

Hines, J.W., & Garvey, D.R. (2007, October). *Data Based Fault Detection, Diagnosis and Prognosis of Oil Drill Steering Systems.* Paper presented at the Maintenance and Reliability Conference. Knoxville, Tennessee, USA.

Hines, J.W., Garvey, J., Preston, J., & Usynin, A. (2008, January). *Empirical Methods for Process and Equipment Prognostics.* Paper presented at 53rd Annual Reliability and Maintainability Symposium. Las Vegas, Nevada, USA.

Hines, J.W., & Usynin, A. (2008). Current Computational Trends in Equipment Prognostics. *International Journal of Computational Intelligence Systems, 1(1)*, 94-102.

Hontelez, J.A.M., Burger, H.H., & Wijnmalen, D.J.D. (1996). Optimum condition-based maintenance policies for deteriorating systems with partial information: *Reliability Engineering & System Safety, 51*, 267-274.

Hussey, A., Lu, B., & Bickford, R. (2009, April). *Performance Enhancement of On-Line Monitoring through Plant Data Classification*. Paper presented at the 6th American Nuclear Society International Topical Meeting on Nuclear Plant Instrumentation, Controls and Human Machine Interface Technology, Knoxville, TN, US.

Jardine, A.K.S., Lin, D., Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition based maintenance. *Mechanical Systems and Signal Processing, 20*, 1483-1510. Venkatasubramanian, V., Rengaswamy, R., Yin, K., Kavuri, S.N. (2003). A Review of Process Fault Detection and Diagnosis Part I and III. *Computers and Chemical Engineering*, *27*, 293-311 and 327-346.

Jarrell, D.B., Sisk, D.R., & Bond, L.J. (2004). Prognostics and Condition-Based Maintenance: A New Approach to Precursive Metrics. *Nuclear Technology, 145*, 275-286.

Joentgen, A., Mikenina, L., Weber, R., & Zimmermann, H.J. (1999). Dynamic Fuzzy Data Analysis based on Similarity between Functions. *Fuzzy Sets and Systems, 105 (1)*, 81-90.

Kliger, S., Yemini, S., Yemini, Y., Oshie, D., & Stolfo, S. (1995). A coding Approach to Event Correlation. In *Proceedings of the 4th International Symposium on Intelligent Network Management* (pp. 266 – 277). London, UK: Chapman and Hall.

Kopnov, V.A. (1999). Optimal degradation process control by two-level policies. *Reliability Engineering & System Safety, 66*, 1-11.

Kozin, F., & Bogdanoff, J.L. (1989). Probabilistic Models of Fatigue Crack Growth: Results and Speculations: *Nuclear Engineering and Design, 115*, 143-171.

Lam, C., & Yeh, R.(1994). Optimal maintenance policies for deteriorating systems under various maintenance strategies: *IEEE Transactions on Reliability, 43,* 423-430.

Laser, M. (2000). Recent safety and environmental l egislation. *Transactions of the Institution of Chemical Engineers, 78(B)*, 419-422.

Lehmann, A. (2006). Joint Modeling of Degradation and Failure Time Data. *Journal of Statistical Planning and Inference, 139(5)*, 1693-1706.

Lu, C.J., & Meeker, W.Q. (1993). Using Degradation Measures to Estimate Time-To-Failure Distribution. *Technometrics, 35(2)*, 161-173.

Marseguerra, M., Zio, E., & Podofillini, L. (2002). Condition-based maintenance optimization by means of genetic algorithms and Monte Carlo simulation: *Reliability Engineering & System Safety, 77*, 151-165.

Muller, A., Suhner, M.C., & Iung, B. (2008). Formalisation of a New Prognosis Model for Supporting Proactive Maintenance Implementation on Industrial System. *Reliability Engineering and System Safety, 93*, 234-253.

Myotyri, E., Pulkkinen, U., & Simola, K. (2006). Application of stochastic filtering for lifetime prediction: *Reliability Engineering System Safety*, *91*, 200-208.
Nimmo, I. (1995). Adequately address abnormal situation operations. *Chemical Engineering Progress, 91(9)*, 36-45.
Orchard, M., Kacprzynski, G., Goebel, K., Saha, B., & Vachtsevanos, G. (2008, October). *Advances in Uncertainty Representation and Management for Particle Filtering Applied to Prognostics*. Paper presented at International Conference on Prognostics and Health Management, Denver, USA.
Oswald, G.F., & Schueller, G.I. (1984). Realiability of deteriorating structures: *Engineering Fracture Mechanics, 20(1),* 479–488.
Pearl J. (1988). *Probabilistic Reasoning in Intelligent Systems*. San Mateo, CA, US: Morgan Kaufmann.
Pecht, M. (2008). *Prognostics and Health Management of Electronics*, New Jersey: John Wiley.
Pedregal, D.J., & Carnero, M.C. (2006). State Space Models for condition Monitoring: A Case Study: *Reliability Engineering and System Safety, 91*, 171-180.
Peel, L. (2008, October). *Data Driven Prognostics using a Kalman Filter Ensemble of Neural Network Models*. Paper presented at the International Conference on Prognostics and Health Management, Denver, CO.
Penha, R.L., & Hines, J.W. (2002). *Hybrid System Modeling for Process Diagnostics*. Proceedings of the Maintenance and Reliability Conference MARCON, Knoxville, USA.
Peng, Y., Zhang, S., & Pan, R. (2010). Bayesian Network Reasoning with Uncertain Evidences, *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 18(5)*, 539-564.
Polikar, R. (2006). Ensemble Based Systems in Decision Making: *IEEE Circuits and Systems Magazine, 6(3)*, 21-45.
Provan, J.W. (1987). *Probabilistic Fracture Mechanics and Reliability*. Dordrecht, PA: Martinus Nijhoff.
Pulkkinen, U. (1991). A Stochastic Model for Wear Prediction through Condition Monitoring. In K. Holmberg and A. Folkeson (Eds.), *Operational Reliability and Systematic Maintenance* (pp. 223-243). London/New York, PA: Elsevier.
Rish, I., Brodie, M., & Ma, S. (2002). Accuracy vs. Efficiency Trade-Offs in Probabilistic Diagnosis. In *Proceedings of the 18th National Conference on Artificial Intelligence.* Edmonton, Canada.
Samanta, P.K., Vesely, W.E., Hsu, F., & Subudly, M. (1991). *Degradation modeling with application to ageing and maintenance effectiveness evaluations*, NUREG/CR-5612. US Nuclear Regulatory Commission.
Saxena, A., Celaya, J., Balaban, E., Goebel, K., Saha, B., Saha, S., & Schwabacher, M. (2008, October). *Metrics for Evaluating Performance of Prognostic Techniques*. Paper presented at International Conference on Prognostics and Health Management. Denver, USA.
Schwabacher, M. (2005, September). *A Survey of Data Driven Prognostics*. Paper presented at AIAAA Infotech@Aerospace Conference, Atlanta, USA.
Schwabacher, M., & Geobel, K. (2007, November). *A Survey of Artificial Intelligence for Prognostics*. Paper presented at the AAAI Fall Symposium, Arlington, Virginia, USA.
Sikorska, J.Z., Kelly, P.J., & McGrath, J. (2010, June). Maximizing the Remaining Life of Cranes in Paper presented at the ICOMS Asset Management Conference, Adelaide, Australia.
Simola, K., & Pulkkinen, U. (1998). Models for non-destructive inspection data: *Reliability Engineering & System Safety, 60*, 1–12.
Singpurwalla, N. (1995). Survival in Dynamic Environments. *Statistical Science, 10(1)*, 86-103.
Singpurwalla, N. (2006). *Reliability and Risk. A Bayesian Perspective*. West Sussex, UK: Wiley & Sons,.
Sobezyk, K., & Spencer, B.F. (1992). *Random fatigue: From data to theory*. Boston, MA, USA: Academic Press.
Sotiris, V., & Pecht, M. (2007, July). *Support Vector Prognostics Analysis of Electronic Products and Systems*. Paper presented at the AAAI Conference on Artificial Intelligence, Vancouver, Canada.
Sotiris, V., Tse, P., & Pecht, M. (2010, June). Anomaly Detection Through a Bayesian Support Vector Machine. *IEEE Transactions on Reliability, 59(2)*, 277-286.

Steinder, M., & Sethi, A.S. (2002). End-to-End Service Failure Diagnosis Using Belief Networks, *Proceedings of Network Operations and Management Symposium*. IEEE Conference Publications.
US Department of Energy (2002, May). *Instrumentation, Controls and Human-Machine Interface*. Presented at the IC&HMI Technology Workshop. Gaithersburg, Maryland, PA:.
Vachtsevanos, G. (2003). Performance Metrics for Fault Prognosis of Complex Systems. In *AUTOTESTCON 2003. IEEE Systems Readiness Technology Conference* (pp. 341-345). IEEE Conference Publications.
Vachtsevanos, G., Lewis, F.L., Roemer, M., Hess, A., & Wu, B. (2006). *Intelligent Fault Diagnosis and Prognosis for Engineering Systems*, 1st edition. Hoboken, NJ, USA: John Wiley & Sons.
Vachtsevanos, G., & Wang, P. (2001). Fault Prognosis Using Dynamic Wavelet Neural Networks. In *AUTOTESTCON Proceedings, 2001. IEEE Systems Readiness Technology Conference* (pp.857-870). IEEE Conference Publications.
Vlok, P.J., Coetzee, J.L., Banjevic, D., Jardine, A.K.S., Makis, V. (2002). An application of vibration monitoring in proportional hazards models for optimal component replacement decisions. *The Journal of the Operational Research Society, 53(2)*, 193-202.
Wang, T., Yu, J., Siegel, D., & Lee, J. (2008, October). *A similarity based prognostic approach for Remaining Useful Life estimation of Engineered Systems*. Paper presented at the International Conference on Prognostics and Health Management. Denver, USA.
Wang, W.Q., Goldnaraghi, M.F., & Ismail, F. (2004). Prognosis of Machine Health Condition using Neuro-Fuzzy Systems. *Mechanical Systems and Signal Processing, 18*, 813-831.
Wang, X., Yu, G., & Lee, J. (2002, September). *Wavelet Neural Network for Machining Performance Assessment and its Implication to Machinery Prognostic.* Paper presented at 5th International Conference on Managing Innovations in Manufacturing (MIM), Milwaukee, Wisconsin, USA.
Yan, J., Koç, M., & Lee, J. (2004). A Prognostic Algorithm for Machine performance Assessment and its Application. *Production Planning and Control, 15(8)*, 796-801.
Yan, J., & Lee, J. (2008, October). *A Hybrid Method for On-line Performance Assessment and Life Prediction in Drilling Operations*. Paper presented at International Conference on Prognostics and Health Management, Denver, USA.
Yeh, R.H. (1997). State-age-dependent maintenance policies for deteriorating systems with Erlang sojourn time distributions: *Reliability Engineering System Safety, 58*, 55-60.
Zhao, X., Fouladirad, M., Berenguer, C., & Bordes, L. (2008, September). *Optimal Periodic Inspection/Replacement Policy of Deteriorating Systems with Explanatory Variables*. Paper presented at the European Safety and Reliability Conference. Valencia, Spain.
Zille, V., Despujols, A., Baraldi, P., Rossetti, G., & Zio, E.(2009, September). *A Framework for the Monte Carlo simulation of Degradation and Failure processes in the assessment of maintenance programs performance*. Paper presented at the European Safety and Reliability Conference, Prague, Czech Republic.
Zio, E. (2006). A Study of the Bootstrap Method for Estimating the Accuracy of Artificial Neural Networks in Predicting Nuclear Transient Processes. *IEEE Transactions on Nuclear Science, 53(3)*, 1460-1478.
Zio, E., & Di Maio, F. (2010). A Data-Driven Fuzzy Approach for Predicting the Remaining Useful Life in Dynamic Failure Scenarios of a Nuclear Power Plant. *Reliability Engineering and System Safety, 95 (1)*, 49-57.

Keywords:
Prognostics: prediction of the state of a system, structure or component.
Degradation Modeling: description of the evolution of change in the performance and functionality of a system, structure or component.
Failure Prediction: task of anticipating when a failure may occur in the future.
Residual Useful Life: usage time remaining before a system, structure or component reaches a state beyond which it cannot longer function as designed.

Condition Monitoring: process of keeping the state of a system, structure or component under check.
Condition-based Maintenance: process of maintenance intervention on a system, structure or component, upon information of its state of condition.