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The challenges of system health management and failure prognostics

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As in Medicine, a clinical picture for diagnosis and prognosis purposes can be made based on the values of some measured parameters related to the health condition of a human being; in many equipments it is also possible to have an idea about its functional condition from the knowledge of the evolution of its significant parameters.

For the aim of system health management, equipment and components are inspected periodically by manual or automatic systems to monitor their condition and to identify their level of degradation. A decision is then taken regarding replacement or maintenance, and this is based upon an analysis of the monitored data. In this view maintenance is carried out when a measurable machine condition shows the need for repair or replacement. This strategy aims at identifying problems in equipment at the early stage so that necessary downtime can be scheduled for the most convenient and inexpensive time. This allows a machine to run as long as it is healthy: equipment is only repaired or replaced when needed as opposed to routine disassembly. By so doing, one aims at achieving maximum availability, minimizing unscheduled shutdowns of production, scheduling maintenance actions as economically as possible.

Usually, the condition of the system concerned is 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. Obviously, the monitoring interval influences the operating cost and overall performance of the plant: a shorter interval may increase the cost of monitoring, whereas a longer one increases the risk of failure.

On the other hand, condition monitoring 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. The first option is to make further investigation of the alarm, without stopping the machine; the second option is to stop the machine for an overhaul of the suspected part. 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.

Furthermore, condition-based maintenance implies that maintenance activities be scheduled in a dynamic way, since the execution times of certain activities will be continually updated as condition information becomes available. Such scheduling is significantly more difficult than scheduling the static policies implied by routine preventive maintenance. Indeed, the dynamic scheduling of condition-based maintenance represents a challenging task which requires the integrated simulation of the system state transitions and the prediction of the monitored physical variables which represent the evolving components condition. Hence, it is important to develop reliable models of components degradation and for the estimation and prediction of its evolution. Given the complexity of the processes underlying mechanical and structural degradation and the ambiguous and uncertain character of the experimental data available, one may have to resort to empirical models based on collected evidence, some of which may very well be of qualitative, linguistic nature. In this direction, soft computing techniques, such as neural networks and fuzzy logic systems (inferential systems based on the mathematics of fuzzy sets), represent powerful tools for their capability of representing highly non-linear relations, of self-learning from data and of handling qualitative information [1]. Embedding these models within the simulation of the stochastic processes governing the system life could represent a significant step forward for the evaluation of the safety and reliability of a system under condition-based maintenance and, thus, for the definition of the optimal thresholds of the monitored variables which determine the dynamic scheduling of maintenance intervention.

From the practical point of view, it is important to note that a condition monitoring system will be efficient only if the information retrieved from the monitoring equipment is relevant and it is filed, processed and used by the management in a timely manner, so that the decisions can have effectiveness and result in an increase of productivity [2]. The capability of acquisition and handling of system and process information in real time is therefore a necessary condition for performing on condition maintenance to optimize the performance of the machines and to maximize their use and productivity.

Extending the potentials behind condition monitoring, failure prognosis is becoming more and more an attractive and challenging task in Reliability, Availability, Maintainability and Safety (RAMS). The primary goal of a prognostic system is to indicate whether the structure, system or component (SSC) of interest can perform its function throughout its lifetime with reasonable assurance and, in case it cannot, to estimate its Time To Failure (TTF), i.e. the lifetime remaining before it can no longer perform its function. The prediction is more effective if informed by measurements of parameters representative of the state of the SSC during its life.

The attractiveness of prognostics comes from the fact that by predicting the evolution of the system dynamic state, it is possible to provide advanced warning and lead time for preparing the necessary corrective actions to maintain the system in safe and productive operation.

However, in real systems often the dynamic states cannot be directly observed; on the other hand, measurements of parameters or variables related to the system states are available, albeit usually affected by noise and disturbances. Then, the problem becomes that of inferring the system state from the measured parameters. Two general approaches exist: i) the model-based techniques, which make use of a quantitative analytical model of the component behavior 0 and ii) the knowledge-based or model-free methods, which rely on empirical models built on available data of the component behavior 00.

The soundest model-based approaches to the state estimation of a dynamic system or component build a posterior distribution of the unknown states by combining the distribution assigned a priori with the likelihood of the observations of the measurements actually collected 00. In this Bayesian setting, the estimation method most frequently used in practice is the Kalman filter, which is optimal for linear state space models and independent, additive Gaussian noises. In this case, the posterior distributions are also Gaussian and can be computed exactly, without approximations.

Yet, in practice the dynamic evolution of many systems and components is non-linear and the associated noises are non-Gaussian 0. Moreover, the problem of state estimation becomes even more complex for hybrid systems, due to the large computational effort needed to keep track of the multiple models of the discrete system modes and the autonomous transitions between them. For these cases, approximate methods, e.g. analytical approximations of extended Kalman (EKF) and Gaussian-sum filters and numerical approximations of the grid-based filters 0 can be used, usually at large computational expenses. Alternatively, one may resort to Monte Carlo sampling methods also known as particle filtering methods, which are capable of approximating the continuous and discrete distributions of interest by a discrete set of weighed ‘particles’ representing random trajectories of system evolution in the state space and whose weights are estimates of the probabilities of the trajectories 00. As the number of samples becomes large, the Monte Carlo approximation yields a posterior pdf representation which is equivalent to its functional description and the particle filter approaches the optimal Bayesian TTF prediction.

The state estimation task becomes quite challenging for systems with a hybrid dynamic behavior characterized by continuous states and discrete modes evolving simultaneously. Sudden transitions of the discrete modes, often autonomously triggered by the continuous dynamics, affect the system evolution and may lead to non-linear behaviors difficult to estimate and predict.
The predictive task must adequately account for the uncertainty associated to the future behavior of the SSC under analysis, in order for the prognostic results to have operational significance, e.g. in terms of maintenance and renovation decisions. Sources of uncertainty derive from: (1) randomness due to inherent variability in the SSC degradation behavior (aleatory uncertainty) and (2) imprecision due to incomplete knowledge and information on the parameters used to model the degradation and failure processes (epistemic uncertainty). While it is commonly accepted that the aleatory uncertainty is appropriately represented by probability distributions, current scientific discussions dispute the potential limitations associated to a probabilistic representation of epistemic uncertainty under limited information. In this respect, a number of alternative representation frameworks have emerged, e.g. fuzzy set theory, evidence theory, possibility theory, interval analysis and imprecise probability.

In conclusion, system health management and failure prognostics have arisen to being a system engineering discipline focused on detection, prediction, and management of the health and status of complex engineered systems. The practical and research interest is quite significant in diverse application areas such as aerospace, transportation, automotive, energy, and industrial automation, as witnessed by the success of PHM08 (Denver, 6-9, 2008), the first international forum dedicated to this emerging discipline.

References

[1] Zio E., Soft Computing Methods applied to condition monitoring and fault diagnosis for maintenance, Proceedings of the Summer Safety and Reliability Seminars, Gdansk/Sopot-Jelitkowo, Poland, July 22-29, 2007.

[2] Roverso D., Hoffmann M., Zio E., Baraldi P., Gola G., Solutions for Plant-Wide On-Line Calibration Monitoring, Proceedings of ESREL 2007, Stavanger, Norway, 25-27 June 2007, Volume 1, pp. 827-832.

[3] A. S. Willsky, A Survey of Design Methods for Failure Detection in Dynamic Systems, Automatica, Vol. 12, 1976, pp. 601-611.

[4] M. Marseguerra, E. Zio, P. Baraldi, I. C. Popescu, P. Ulmeanu, A Fuzzy Logic – based Model for the Classification of Faults in the Pump Seals of the Primary Heat Transport System of a Candu 6 Reactor", Nuclear Science and Engineering, Vol. 153, No. 2, pp. 157-171, 2006.

[5] J. Reifman, Survey of Artificial Intelligence Methods for Detection and Identification of Component Faults in Nuclear Power Plants, Nucl. Technol., 119, 76 ~1997.

[6] A. Doucet, On Sequential Simulation-Based Methods for Bayesian Filtering, Technical Report, University of Cambridge, Dept. of Engineering, CUED-F-ENG-TR310, 1998.

[7] A. Doucet, J.F.G. de Freitas and N.J. Gordon, An Introduction to Sequential Monte Carlo Methods, in Sequential Monte Carlo in Practice, A. Doucet, J.F.G. de Freitas and N.J. Gordon, Eds., New York: Springer-Verlag, 2001.

[8] G. Kitagawa, Non-Gaussian State-Space Modeling of Nonstationary Time Series, Journal of the American Statistical Association, Vol. 82, 1987, pp. 1032-1063.

[9] B.D. Anderson and J.B. Moore, Optimal Filtering, Englewood Cliffs, NJ: Prentice Hall, 1979.

[10] P.M. Djuric, J.H. Kotecha, J. Zhang, Y. Huang, T. Ghirmai, M. F. Bugallo, J. Miguez, Particle Filtering, IEEE Signal Processing Magazine, 2003, pp. 19-37.

[11] A. Doucet, S. Godsill and C. Andreu, On Sequential Monte Carlo Sampling Methods for Bayesian Filtering, Statistics and Computing , Vol 10, 2000, pp. 197-208.