8th. World Congress on Computational Mechanics (WCCM8)
5th. European Congress on Computational Methods in Applied Sciences and Engineering (ECCOMAS 2008)
June 30 – July 5, 2008
Venice, Italy

ONLINE ESTIMATION OF FATIGUE CRACK GROWTH BY MONTE CARLO-BASED FILTERING

***F. Cadini[1], E.Zio[2] and D. Avram[3]**

[1] Polytechnic of Milan
via Ponzio 34/3
20133 Milan Italy
francesco.cadini@polimi.it

[2] Polytechnic of Milan
via Ponzio 34/3
20133 Milan Italy
enrico.zio@polimi.it

[3] Politehnica University of Timisoara
Bd. Vasile Parvan 2 300223
Timisoara Romania
avram.diana@gmail.com

Key Words: *Crack growth estimation, robust lifetime prediction, uncertainty assessment, Monte Carlo, Particle Filtering.*

ABSTRACT

For a certain class of industrial and structural components, fatigue crack growth is the typical degradation process [1]. During the operation phase, monitoring of this process allows anticipating the components' evolution to failure.

In practice, a robust prediction of the remaining lifetime of these components, with an estimate of its related uncertainty, may be difficult to obtain since the components' degradation state may not be directly observable and/or the measurements may be affected by noise and disturbances. In these cases, model-based estimation methods aimed at inferring the dynamic degradation state on the basis of a sequence of noisy measurements, seem to offer interesting potentials for successful applications, ensuring a reliable quantification of the uncertainty associated to the prediction.

The soundest approaches of this kind rely on Bayesian methods to combine a prior distribution of the unknown degradation states with the likelihood of the observations collected, to build a posterior distribution [2] [3]. In this 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 [4]. In this case, the posterior distributions are also Gaussian and computed exactly, without approximations.

On the other hand, in most realistic cases the dynamics of degradation is non-linear and/or the associated noises are non-Gaussian. Various approximate methods can be proposed to tackle these cases, e.g. the analytical approximations of the extended Kalman (EKF) and the Gaussian-sum filters and the numerical approximations of the grid-based filters [4]. Recently, Monte Carlo sampling methods are gaining popularity for their flexibility and ease of design [5]. These methods go under the name of particle filtering because the continuous distributions of interest are approximated by a discrete set of weighed particles, where each particle represents a random trajectory of evolution in the state space and the weight is the probability of the trajectory [6] [7].

In this work we apply a particle filtering algorithm for predicting the non-linear structural response of a component subject to fatigue crack growth [9]. The approach allows estimating the crack depth evolution and predicting the component's remaining lifetime, with the adequate quantification of the associated uncertainties.

The simulation method is capable of handling nonlinear dynamics and of dealing with non-Gaussian noises at no further computational or design expenses. As such, it represents a robust prediction tool which can drive effective on-line strategies for improving reliability, safety and cost effectiveness.

REFERENCES

[1] M. M. Rocha, G. I. Schueller, "A Probabilistic Criterion for Evaluating the Goodness of Fatigue Crack Growth Models", *Engineering Fracture Mechanics*, Vol.**53**, pp. 707-731 (1996).

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

[3] 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).

[4] B.D. Anderson and J.B. Moore, "Optimal Filtering", Englewood Cliffs, NJ: Prentice Hall (1979).

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

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

[7] A. Doucet, S. Godsill and C. Andrieu, "On Sequential Monte Carlo Sampling Methods for Bayesian Filtering", *Statistics and Computing*, Vol. **10**, pp. 197-208 (2000)

[8] E. Myotyri, U. Pulkkinen, K. Simola, "Application of stochastic filtering for lifetime prediction", *Reliability Engineering and System Safety*, Vol. **91**, pp. 200-208 (2006).