

Machine learning and Prognostic for complex systems considering environmental conditions: application on wind turbines

Edith Grall and Mitra Fouladirad
Laboratoire Informatique et Société Numérique
Université de Technologie de Troyes

1 Subject

Motivation

In complex system specially in energy production systems, the failure prediction and maintenance planning are major elements to reduce economic and energy losses. To predict the failure of the system or one of its components it is necessary to have knowledge about the future behaviour of the system. In this purpose, a health indicator should be extracted and a mathematical model could be associated to its evolution and based on this model the future behaviour can be estimated. Usually, complex systems such as wind turbine or their components are subject to degradation influenced by several factors which cannot be all listed and their impacts cannot be necessarily modelled with a deterministic expression. That is why the degradation phenomenon could be seen as random and can be modelled by probabilistic tools. Stochastic processes are suitable tools to model this random evolution in time. The choice of an appropriate model for an degradation phenomenon is not an easy task and it depends on several aspects: the type of the components, the available information on the system (degradation or only failure), the point of view on the system (multi-component vision or one block vision), the dependency between the components of a system, the type of maintenance performed (corrective, preventive, planned, condition-based...), the type of equipment considered (specific individual or fleet of homogeneous materials), the nature of available information (censored, incomplete data, abundant or rare).

The first step for degradation modelling is to analyse the available data on the degradation, failure times, the maintenance dates and operational environment. Based on the available historical data a mathematical model can be proposed to predict the future behaviour of the system, to forecast the failure and to evaluate the associated uncertainties. Nowadays, partly due to the massive automation of all processes (abundance of sensors), the development of modern communication means and a high demand on high frequency information, the data analysis should deal with large scale data in a level never reached before. This high demand on instantaneous and reliable information has encouraged to find alternative data treatment methods. Machine learning techniques permit to treat efficiently the available information and build a health indicator. Moreover, these methods permit a better condition-monitoring of complex systems (where the system health indicator is monitored during its lifetime by numerous sensors) and lead to more reliable and sustainable systems. Monitoring data on the system or on its environmental conditions are used for maintenance planning in order to avoid failure or productivity losses.

General layout of the thesis

In a on-shore or offshore wind farm, different sensors are installed and permit the health monitoring. The farm, the wind turbines, their components and the environmental conditions are monitored continuously or by inspections. The available data could give the state of a health or performance indicator of the system. Based on the available historical data, the degradation of wind turbines, the wind speed and its impact on the degradation are modelled. Based on this latter and the information collected through monitoring, the remaining useful lifetime are sequentially estimated. After each estimation, a maintenance action can be planned to avoid the failure and to reduce the risk occurrence of critical events. The study of the failure probabilities estimation permits to propose confidence intervals for the prediction results.

There are preliminary results on each of the points highlighted above, for instance refer to [4, 5]. These results can be considered as a starting point to enhance the models and their performances.

The different steps of this thesis can be resumed as follows

1. Data management: to gather available data on degradation and environment etc.
2. Data analysis: the application of machine learning techniques for health indicator classification according to the undergoing environmental condition
3. Degradation modeling: to propose a stochastic model able to capture the degradation features taking into account the impact of environmental condition
4. Prognostic: Remaining useful lifetime estimation based on the stochastic model properties.
5. Predictive maintenance: using the results during the prognostic step.
6. Application to wind turbine system with wind data.

The key knowledge and required skills to implement the previous steps are as follows:

1. Statistical data analyses tools
2. Statistical inference, classification
3. Simulation and programming software: R, Python, Matlab, Scilab, etc..

Main collaboration on the subject

The candidate will organise and/or participate to meetings or seminars with the major industrial partners of the UTT on this subject.

2 Research team

Edith Grall research interests focus on machine learning, supervised and unsupervised data classification, (see references [8–12]) Mitra Fouladirad research interests focus on degradation modeling using stochastic models for joint maintenance/monitoring optimisation (see references [1–7]). Contacts: **mitra.fouladirad@utt.fr**, **edith.grall@utt.fr** (refer to www.researchgate.net for more details)

Research team

The Systems Modelling and Dependability Laboratory (webpage: <http://lm2s.utt.fr/en/index.html>) is part of the LIST3N department. The Systems Modelling and Dependability is organised into two main research projects: decision and diagnostic in non-stationary environment and stochastic models for reliability and maintenance. The applicant will be involved in the last team.

National collaborations

GIPSA-INP Alpes Grenoble University, Electricity of France, Biofortis, IFP Energies nouvelles.

International collaborations

What is more The candidate will be able to work with the usual international partners of the supervisors on the subject that is the research teams of:

- W. Meeker Iowa State University, Iowa, USA (wqmeeker@iastate.edu)
- M. Xie from Hong Kong University, China (minxie@cityu.edu.hk)
- David Coit Rutgers University USA
- Alfredo Arcos Jiménez Universidad de Castilla La Mancha
- Adrian Stetco University of Manchester

If necessary, a research stay in one of these universities can be organised. Moreover, if the quality of the work is correct, any Ph.D student of the team attends international conferences during the thesis.

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