

AN ADVANCED EARLY FAULT DETECTION TOOL FOR PREDICTIVE MAINTENANCE OF A FLEET OF INDUSTRIAL GAS TURBINES

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ABSTRACT

Manufacturers of gas turbines for energy production are shifting their business from selling the turbines to selling the energy production rate, with heavy economic penalties whenever the rate requirement is not achieved. Predictive maintenance becomes mandatory for this new business, to profitably manage gas turbine fleets. Predictive maintenance allows early detecting the incipient degradation process of the turbine, assessing the turbine degradation state, predicting the future degradation evolution toward failure and, on the basis of the predictions, optimizing fleet operation by a proper, dynamic scheduling of the maintenance interventions. In this work, we propose a tool that exploits IoT devices for remotely monitoring the turbines and dedicated advanced statistical and machine learning algorithms for the treatment of the information contained in the data, with the objectives of early detecting the turbines incipient degradation, thus providing early alert messages to the operators. Based on this information, the operators can intervene by promptly maintaining the degrading turbines for reducing the maintenance intervention times, increasing the fleet overall availability and avoiding severe, if not catastrophic, consequences. The tool for Early Fault Detection is therefore expected to yield a profit improvement for both the turbine manufacturers and energy producers.

INTRODUCTION

The digital revolution enabled by the continuously increasing affordability of Internet of Things (IoT) devices and cloud infrastructures is at the basis of Industry 4.0, the fourth industrial revolution: smart and connected IoT devices continuously acquire condition monitoring data of components and systems, which are made available in the cloud for use by business analytics.

One main technological breakthrough brought by the availability of this huge amount of collected information,

is the development of accurate and continuously improving Predictive Maintenance (PM) tools for the detection of incipient failures, the diagnosis of the health condition of the monitored equipment and the prediction of its expected failure time. The set of detection, diagnostic and prognostic tasks is often referred to as Prognostics and Health Management (PHM), (Simões et al., 2011; Wang, 2002; Zio, 2006; Pecht, 2009).

The potential benefits brought by the accurate application of these tasks is disruptive, as they allow setting efficient, just-in-time and just-right maintenance strategies; in other words, providing the right part to the right place at the right time. This opportunity is big, because doing this would maximize production profits and minimize all costs and losses, including asset ones. Despite the importance of the issue, to the authors' best knowledge a full-fledged commercial prognostics tool for gas turbines is currently not available, whereby turbine maintenance still relies on a combination of condition-based and scheduled tasks. Nonetheless, the continuously increasing data availability is steering research effort toward the development of tools enabling the application of Predictive Maintenance (e.g., Jardine et al., 2006; Dragomir et al., 2009; Zio, 2013).

In this work, we concentrate on the first step of PHM, i.e., detection, which turns the light on the critical components of the asset to promptly provide the information necessary for being prepared to the future evolution of their degradation.

Generally, one main issue for detection on complex industrial systems such as gas turbines, is to give due account to the variability of the operating and ambient conditions, which can affect the behavior of the monitored signals so that they might hide the degradation effect; this makes very difficult the prompt detection of an anomalous behavior. To address this issue, we develop a Fault Detection Tool (FDT) capable of early detecting

degradation on the monitored component, whichever the environmental and operating conditions are.

The paper structure can be summarized as follows: the Introduction presents the industrial context of the paper; the Fault Detection Tool: Performance Requirements Section introduces the requirements for the development of a FDT; the Fault Detection Tool: Methodological Approach Section presents the details of the methodologies at the basis of our FDT; the PM Tool: Practical Applications Section shows two practical applications of the developed FDT to real industrial cases regarding the Predictive Maintenance of Gas Turbines for energy production; finally, conclusions and remarks are drawn in the Conclusion Section.

FAULT DETECTION TOOL: PERFORMANCE REQUIREMENTS

The objective of fault detection is to alert the asset manager at the beginning of a degradation process occurring on the monitored component: the more accurate the fault detection, the closer is the detection time to the real onset of the component degradation.

Two possible scenarios originate from an erroneous fault detection:

- A false alarm is triggered, which occurs in the case of conservative over-estimations of the anomalous conditions (Chetouani, 2006);
- An alarm is missing, which occurs in the opposite case: under-estimation of the anomalous conditions (Arinton et al., 2012; Di Maio et al., 2013).

Certainly, an important additional issue is that of isolating the failure of a sensor from that of the monitored system. This sensor validation issue is discussed in (Nair et al., 2016; Baraldi et al., 2011c), and it is not the focus of this paper.

One of the most important aspects regarding the definition of the performance requirements of a FDT consists in the identification of acceptable rates of false and missing alarms, which are often referred to as false positive and false negative rates, respectively. Detection promptness is not discussed in this paper, since we present only one failure trajectory.

These requirements depend on the specific situation. For example, in safety critical contexts, false alarms are more tolerated than missing alarms, as it is of paramount importance to avoid critical situations. On the other hand, in production contexts in which the availability is the main concern, such as in an industrial assembly line, then missing alarms are tolerated more than false alarms. Figure 1 summarizes the possible different situations in which we might be applying a Fault Detection Tool.

In the following Section, we detail the techniques at the basis of the proposed FDT and we show how to set their parameters for meeting the requirements on the FDT false positive and false negative rates. We also provide guidelines for the selection of the most suited

methodological approach of the FDT to be selected according to the specific considered situation

FAULT DETECTION TOOL: METHODOLOGICAL APPROACH

The practical development of a FDT heavily depends on the available knowledge, information and data. We want to build a data-driven FDT (Baraldi et al., 2013), whereby the techniques to be used depend on which of the following two cases we are coping with:

- Only data corresponding to the healthy system behavior are available. This situation is typical of new industrial assets, which have not experienced significant degradation.
- Data of both healthy and degrading conditions of the system are available. This situation is more frequent in contexts where the degradation to be detected does not have catastrophic consequences, such as the degradation mechanisms leading to trip of turbines operating in power generation plants in de-rated settings.

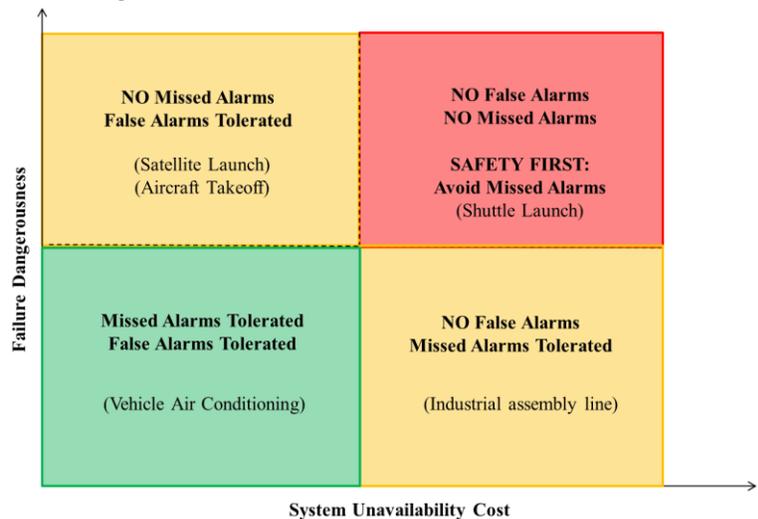


Figure 1. Identification of the situation based on the failure dangerousness and on the unavailability costs

In the next sub-Sections, we describe the techniques which our FDT relies on to address these two cases.

FDT based on healthy data only

To develop a fault detection framework in this setting, we rely on a residual approach followed by a statistical test on the computed residuals to detect whether the turbine behavior is healthy or degraded (Figure 2).

Namely, the residual approach uses the available healthy data to train signal reconstruction models, which provide the reconstruction of the healthy expected behavior of the turbine's signals given the observed behavior. This reconstruction is at the basis of the detection of anomalous conditions: a small difference between the observed and the reconstructed signals (i.e., the computed residuals are low) is indicative of a healthy state of the

turbine, whereas when this difference becomes significant (i.e., the computed residuals are large), it generally indicates an anomalous behavior of the turbine.

To robustly evaluate if the computed residuals are representative of an anomalous behavior, we apply a statistical test for identifying whether the residual has changed with respect to its healthy distribution, thus indicating the possible presence of an incipient degradation mechanism affecting the turbine.

Different models can be used for both signals reconstruction and residual changes detection. In our FDT

tool, we apply the following three techniques for signal reconstruction: Principal Component Analysis (PCA), Self-Organizing Maps (SOMs) and Auto-Associative Kernel Regression (AAKR). The detailed description of the statistical base of the models implemented in the FDT tool is outside the scope of the present paper. Each of these techniques is characterized by strengths and weaknesses, which can be evaluated by considering the following reconstruction metrics:

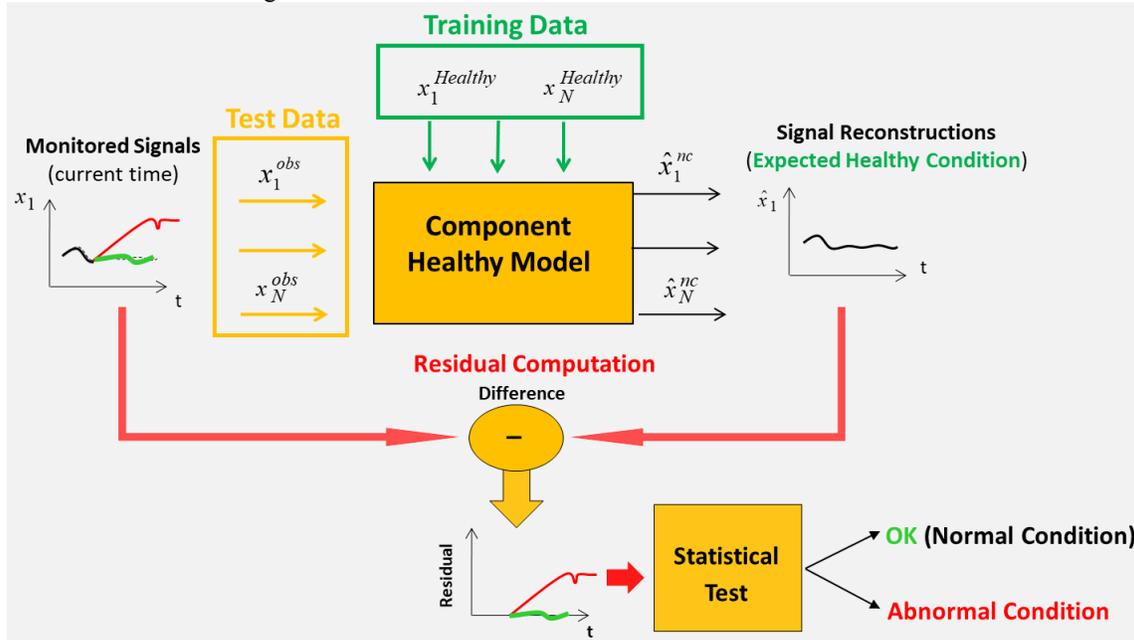


Figure 2. Sketch of the FDT for healthy data

- **Reconstruction Accuracy:** the ability of the model to correctly and accurately predict the signal values when the plant is in normal operation. An accurate condition monitoring model allows reducing the number of false alarms, i.e. detections of faulty behaviors when no faulty conditions are actually occurring.
- **Reconstruction Robustness:** the model ability to reconstruct the values of the signals of interest in abnormal operation, when some monitored parameters behave anomalously. In abnormal plant conditions, a robust model reconstructs the value of a plant signal as if the plant were in normal operation. Then, the differences between the measured and the reconstructed signal values can easily identify the abnormal condition.
- **Reconstruction Spillover:** it measures the effect that the anomalous behavior of a monitored signal in abnormal operation has on the estimation of the other healthy signals.

The three implemented reconstruction models are characterized by different performance in terms of Accuracy, Robustness and Spillover, and therefore they

can be used in different conditions, according to the desired performance.

Finally, the statistical test implemented in this tool for the detection of the change of the residuals' distribution is the Z-Test, which does not require any hypothesis on the distribution of the residuals and, therefore, can be applied to several different situations.

The techniques implemented in the FDT for signal reconstruction are the following:

Principal Component Analysis (PCA)

PCA has been widely used in PHM for fault detection (Hines et al., 1996; Hines et al., 2006; Zhang et al., 2011).

- **Advantages:** PCA is computationally very fast, and provides very accurate reconstructions.
- **Drawbacks:** PCA reconstruction accuracy can be compromised when the relationships among the different available signals are non-linear. Its inferential properties might confuse a deviation due to degradation with a deviation due to different operating conditions. In this case, the residual values do not allow a fast fault detection.

Self-Organizing Maps (SOM)

SOMs (Kohonen, 1998) have been successfully applied to fault detection in many industrial fields (Qui et al., 2004; Huang et al., 2007, Rigamonti et al., 2016). They allow reconstructing the signal behavior and automatically clustering the different operating conditions of the considered turbine.

- **Advantages:** SOM is able to deal with noisy signals and is not severely affected by the presence of outliers in the training data. It allows automatically create a model of the turbine healthy behavior in variable operating conditions. SOM provides very robust signal reconstructions, thus reducing the risk of missed alarms.
- **Drawbacks:** the SOM architecture is defined by several parameters, which need to be properly set in order to obtain a model suited for the specific application. SOM cannot infer the behavior of healthy signals outside the training range and, generally, it provides less accurate reconstruction than those provided by PCA.

Auto-Associative Kernel Regression (AAKR)

AAKR (Baraldi et al., 2011a) has been widely used and exploited for fault detection in energy production plants (Baraldi et al., 2012).

- **Advantages:** easy to implement and to set, AAKR allows the specific investigation of the behavior of each signal which can be considered as representative of the turbine behavior. It allows a fast identification of the drift of the component behavior from its healthy conditions.
- **Drawbacks:** It is computationally intensive when taking into account large datasets. Furthermore, it allows detecting a change of behavior, but it doesn't allow reconstruct the healthy signals when their values, due to novel operating or environmental conditions exceed the range described by the training data.

Z-Test

The Z-Test requires that the sample mean and standard deviation of a given population be known (Kirk, 1999). These are estimated using a sliding window technique (Figure 3). A small sliding window, W_2 , is used to estimate the current mean $\mu_r(t)$ of a residual signal, i.e. the difference between the collected signal and the corresponding reconstruction of its expected healthy behavior, whereas the standard deviation of the nominal residual signal, $\sigma_r(t)$, is computed on a window W_1 preceding W_2 , where $W_1 \gg W_2$. W_1 is offset by W_2 by a buffer W_{Delay} , to ensure that W_1 does not contain any samples after fault occurrence.

We assume that there is a fault whenever $\mu_r(t)$ lies outside of the upper and the lower thresholds, ε_r^- and ε_r^+ . Parameters W_1 , W_2 , W_{Delay} , ε_r^- and ε_r^+ are experimentally tuned to optimize the fault detection performance, i.e., minimize false alarms, while keeping detection sensitivity high (Biswas et al., 2003).

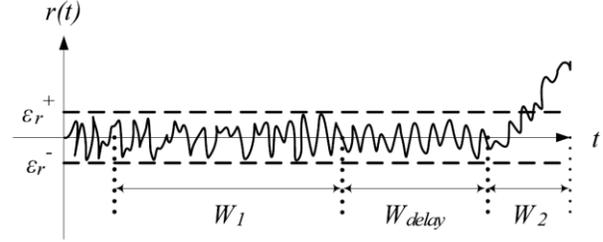


Figure 3 – Sliding windows in the fault detection scheme

FDT based on healthy and degraded data

When the data collected on the turbine concern both the healthy conditions and degraded state, it is possible to develop a FDT framework that allows not only detecting an anomalous behavior of the turbine, but also to assess its level of degradation, i.e. to estimate the current level of the turbine's degradation evolution and to evaluate the associated failure risk.

This approach is constituted by three sequential modules as shown in Figure 4: the feature extraction module, the feature selection module and the classifier. The objective is to extract and identify significant features which are invariant to the different turbine's operating conditions: these features contain the informational content for distinguishing among the different degradation levels of the turbine. These features are monotone with the turbine's degradation, thus enabling the classifier to both detect a possible anomalous behavior and estimating the associated degradation level, which is here defined as the percentage of its drift from its nominal healthy behavior to its failure. Notice that we are not considering all the possible failure mechanisms, neither all the possible features. We just identified this behavior in the field data used for the tool development. When new data will be available, we will search for features with the same characteristics of those described in this paper. It is worth noting also that in order to develop this FDT approach, the available data for the model training need to be associated with an a priori known label representing the corresponding degradation class, which is a qualitative indication of the level of degradation at which the turbine is considered to operate, e.g., healthy, partially degraded, severely degraded. This degradation class will be used for the tuning and the optimization of both the feature selection and the classifier modules.

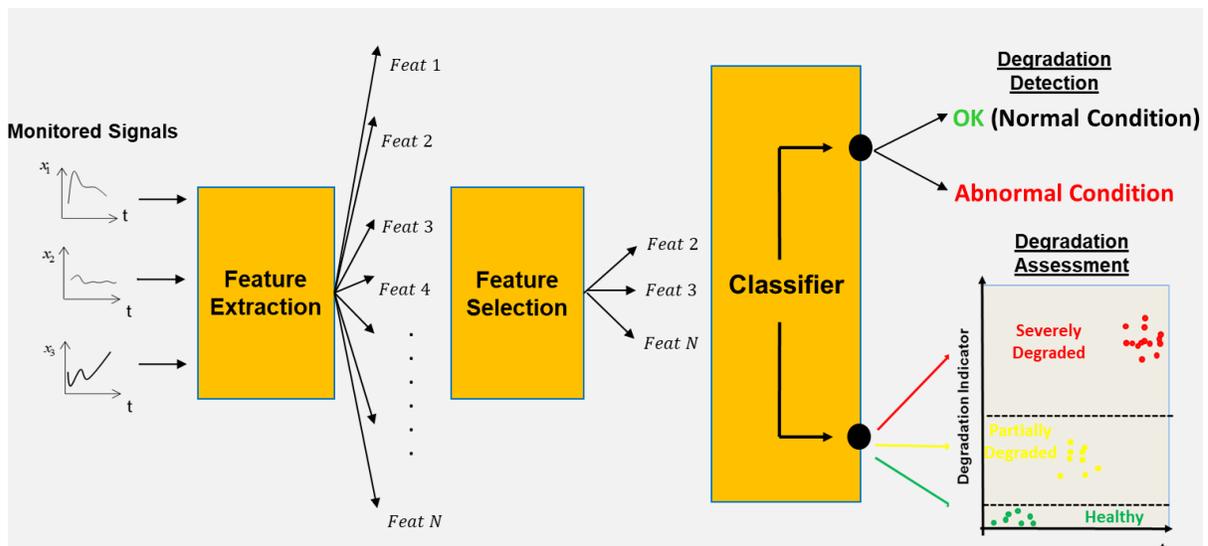


Figure 4. Sketch of FDT for healthy and degraded data

Feature Extraction Module

The Feature Extraction module receives as input the raw signals collected from the turbine and compute a wide range of different features, such as statistical features (i.e., mean, standard deviation, skewness, etc.), Fourier Transforms and Wavelet Transforms. These features can be computed over either a sliding window or on the whole signal's length. To be robust, this set of features has to be as wide as possible, thus including a very large number of features which might be useless for a specific application: the next module identifies and select only the significant features for the considered application.

Feature Selection

This module receives as input all the features extracted by the previous module, together with the associated label indicating the corresponding degradation level. Then, it assesses the extracted features with respect to performance metrics, such as feature monotonicity and trendability. This step leads to the elimination of the uninformative features and to the selection of those significant for classification, which are fed as input to the classifier.

Classifier

Once the significant features are identified and selected by the Feature Selection module, the turbine's health conditions are automatically assessed through a classifier. We developed an ANN for detecting the turbine's incipient degradation and estimating its degradation level. Based on the information contained in the selected features, the classifier is expected to provide accurate information regarding the component degradation.

PM TOOL: PRACTICAL APPLICATIONS

The developed FDT has been successfully applied to different real industrial applications. In this Section we present two applications: the first concerns an industrial gas turbine operating in variable but stationary conditions, for which only healthy data are available; the second

application concerns the vibration signals collected during the shut-down transients of a gas turbine in both healthy and degraded states, obtaining an accurate classification of the turbine aging.

For confidentiality, we cannot provide detailed information regarding the available data, neither about the type of turbine which we have considered.

Practical Application 1

We considered the data collected on an industrial gas turbine over 6 months of operation. The considered dataset included 155 signals, i.e., operating condition, temperature and vibration signals. Every collected data consisted in an average of the raw data on a 5 minute window, thus resulting in 40 thousand available patterns. The considered case study is characterized by very different operating and environmental conditions, which significantly influence the behavior of the collected signals. These conditions change slowly over time, whereby we can assume that the data acquisition frequency of once every 5 minutes is a good compromise solution between the need of collecting full information and that of reducing the acquisition and storage costs. To cope with this situation, we resorted to the residual approaches previously described and, due to the critical unavailability costs characteristic of an industrial gas turbine (i.e., in the range of million dollars per day), we specifically selected the PCA for its intrinsic accuracy characteristics, which guarantee a very low rate of false alarms due to inaccurate signals reconstruction.

We trained the model using only the data which have been recognized as healthy by the manufacturer. Then, we computed the signals residual and applied the Z-Test. The obtained results are shown in Figure 5: we identified an elbow point in the residuals, i.e. a sharp acceleration of the residuals values, which indicates the early beginning of an accelerated component degradation. This degradation onset has been promptly detected by the Z-Test (represented by

the step in the red thick line). Notice that the FDT allowed the degradation detection one month and a half in advance with respect to the triggered alarm: the FDT can provide useful insights to the field operators, who can rely on a auxiliary useful aid in the maintenance decision making process.

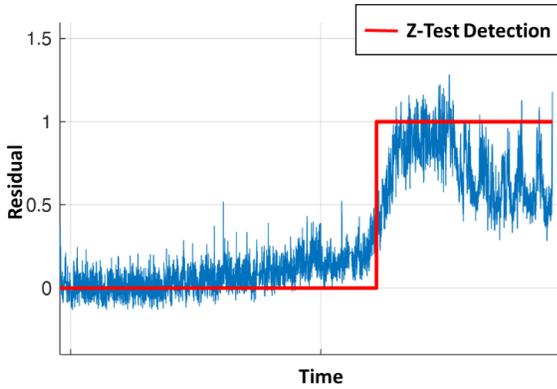


Figure 5. Results of Application 1

Practical Application 2

We considered the vibration data collected at the sampling frequency of 10 KHz during 31 shutdown transients of the same industrial gas turbine considered above. Differently from the previous Section, in this case a label corresponding to the turbine aging was associated to each transient data. The oldest data were classified as healthy, whereas the last data before the turbine failure were considered as very degraded. We defined a monotonic temporal classification of the degradation corresponding to the considered transient, and we exploited this supervised classification in order to develop a model for the assessment of the turbine degradation.

The available vibration signals have been fed to a feature extraction module which, in this case, has computed a hundred different features, i.e. statistical features, wavelet transforms, Fourier transforms, etc. The feature extraction module provided a large number of features for each signal, leading to the availability of more than ten thousand extracted features. A classic approach for the identification of the significant features to consider, such as a genetic or an optimization algorithm (Baraldi et al., 2011b), would have been too much computationally intensive, resulting in a very inefficient approach. Therefore, we fed the extracted features to a feature selection module which, by computing different metrics especially tailored to our needs, have been able to identify a much smaller subset of features (i.e., 60 features). Once this subset has been identified, we developed a wrapper approach, i.e. a supervised approach which aims at selecting the classifier input features based on the computed classification performance (Baraldi et al., 2011b). This allowed us to develop a ANN classifier with optimal performance. For confidentiality, we cannot provide the details of the selected features nor of the selected signals. Figure 6 shows a masked version of one

of the most significant features, which allowed us to accurately assess the degradation state of the turbine based on its vibration transient behavior.

Namely, Figure 6 shows the values of the feature extracted in the first 5 transients (green dots), in the 5 central transients (red dots) and in the last 3 transients (black dots), according to the temporal order of the transients and, therefore, to their degradation levels. Notice that by only looking at this identified feature, it is possible to clearly distinguish among the three defined degradation classes. Furthermore, given the monotonicity of the identified feature, it would be possible in the future to consider it for the development of a predictive model for the estimation of the Remaining Useful Life (RUL) of the gas turbine.

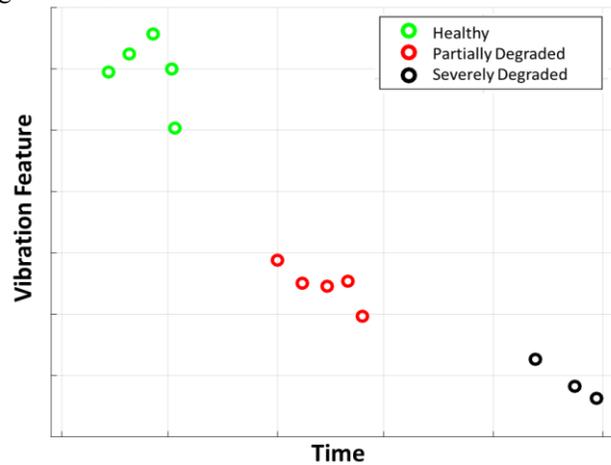


Figure 6. Results of Application 2

CONCLUSIONS

In this paper, we presented a FDT for industrial gas turbines. The developed tool encodes two different approaches, which can be exploited depending on the data availability and on the industrial practical requirements: the first approach can be applied in case only the healthy data of the turbine are available to detect the turbine's degradation onset, and it can be customized on the specific industrial (i.e., avoiding false alarms rather than missed alarms). The second approach requires the availability of both healthy and degraded data, each of them associated to a label representing the corresponding turbine's degradation level. It is more complex to develop, but it provides more information about the turbine degradation state, as it allows both distinguishing between healthy and degraded behavior and assessing the corresponding degradation level.

Two examples of the results of the FDT application of both these approaches to real industrial cases concerning an industrial gas turbine have been presented. The results have shown the potentialities of the developed Predictive Maintenance Tool, glimpsing the wide area of application suitable for the Tool and the significant added values which it can provide to the monitoring and maintenance operations of a large fleet of gas turbines for energy production.

NOMENCLATURE

AAKR: Auto Associative Kernel Regression
ANN: Artificial Neural Network
FDT: Fault Detection Tool
PHM: Prognostic and Health Management
PM: Predictive Maintenance
PCA: Principal Component Analysis
RUL: Remaining Useful Life
SOM: Self-Organizing Maps

REFERENCES

- (Arinton et al., 2012) Arinton, E., Caraman, S., & Korbicz, J. (2012). Neural networks for modelling and fault detection of the inter-stand strip tension of a cold tandem mill. *Control Engineering Practice*, 20(7), 684-694.
- (Baraldi et al., 2011a) Baraldi, P., Compare, M., Despujols, A., & Zio, E. (2011). Modeling of the effect of maintenance actions on the degradation of an electric power plant component. *Proceedings of the Institution of Mechanical Engineers. Part O, Journal of Risk and Reliability*, 225(2), 169-184.
- (Baraldi et al., 2011b) Baraldi, P., Canesi, R., Zio, E., Seraoui, R., & Chevalier, R. (2011). Genetic algorithm-based wrapper approach for grouping condition monitoring signals of nuclear power plant components. *Integrated Computer-Aided engineering*, 18(3), 221-234.
- (Baraldi et al., 2011c) Baraldi, P., Gola, G., Zio, E., Roverso, D., Hoffmann, M. (2011). A randomized model ensemble approach for reconstructing signals from faulty sensors". *Expert Systems with Applications*, 38(8), pp. 9211-9224.
- (Baraldi et al., 2012) Baraldi, P., Di Maio, F., Pappalione, L., Zio, E., & Seraoui, R. (2012). Condition monitoring of electrical power plant components during operational transients. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 226(6), 568-583.
- (Baraldi et al., 2013) Baraldi, P., Cadini, F., Mangili, F., & Zio, E. (2013). Model-based and data-driven prognostics under different available information. *Probabilistic Engineering Mechanics*, 32, 66-79.
- (Biswas et al., 2003) Biswas, G., Simon, G., Mahadevan, N., Narasimhan, S., Ramirez, J., & Karsai, G. (2003, June). A robust method for hybrid diagnosis of complex systems. In *Proceedings of the 5th Symposium on Fault Detection, Supervision and Safety for Technical Processes* (pp. 1125-1131).
- (Chetouani, 2006) Chetouani, Y. (2006). Fault detection in a chemical reactor by using the standardized innovation. *Process Safety and Environmental Protection*, 84(1), 27-32.
- (Di Maio et al., 2013) Di Maio, F., Baraldi, P., Zio, E., & Seraoui, R. (2013). Fault detection in nuclear power plants components by a combination of statistical methods. *IEEE Transactions on Reliability*, 62(4), 833-845.
- (Dragomir et al., 2009) Dragomir, O.E., Gouriveau, R., Dragomir, F. Minca, E., Zerhouni, N. (2009). Review of prognostic problem in condition-based maintenance, *IEEE Control Systems Society. European Control Conference, ECC'09, Aug 2009*, Budapest, Hungary, pp.1585-1592.
- (Jardine et al., 2006) 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, pp. 1483-1510.
- (Hines et al., 1996) Hines, J. W., Wrest, D. J., & Uhrig, R. E. (1996, September). Plant wide sensor calibration monitoring. In *Intelligent Control, 1996., Proceedings of the 1996 IEEE International Symposium on* (pp. 378-383).
- (Hines et al., 2006) Hines, J. W., & Seibert, R. (2006). *Technical Review of On-Line Monitoring Techniques for Performance Assessment. Volume 1. State-of-the-Art*.
- (Huang et al., 2007) Huang, R., Xi, L., Li, X., Liu, C. R., Qiu, H., & Lee, J. (2007). Residual life predictions for ball bearings based on self-organizing map and back propagation neural network methods. *Mechanical Systems and Signal Processing*, 21(1), 193-207.
- (Kirk, 1999) Kirk, R., (1999). *Statistics, An Introduction*. Fort Worth, TX: Harcourt Brace, 1999.
- (Kohonen, 1998) Kohonen, T. (1998). The self-organizing map. *Neurocomputing*, 21(1), 1-6.
- (Nair et al. 2016) Nair, A., Boring, S., Coble, J. (2016). High accuracy signal validation framework for sensor calibration assessment in NPPs, *Transactions of the American Nuclear Society*, Vol. 115, pp. 348-351.
- (Pecht, 2009) Pecht, M. (2009). *Prognostics and Health Management of Electronics*, John Wiley & Sons, Encyclopedia of Structural Health Monitoring.
- (Qui et al., 2004) Qui, H., & Lee, J., (2004, December). Feature fusion and degradation using self-organizing map. In *Machine Learning and Applications, 2004. Proceedings. 2004 International Conference on* (pp. 107-114). IEEE.
- (Rigamonti et al., 2016) Rigamonti, M., Baraldi, P., Zio, E., Alessi, A., Astigarraga, D., & Galarza, A. (2016). Identification of the degradation state for condition-based maintenance of insulated gate bipolar transistors: A self-organizing map approach. *Microelectronics Reliability*, 60, 48-61.
- (Simões et al., 2011) Simões, M.M., Gomes, J.M., Yasin, C.F. (2011). A literature review of maintenance performance measurement: A conceptual framework and directions for future research, *Journal of Quality and Maintenance Engineering*, 40, 116-137.
- (Wang, 2002) Wang, H. (2002). A survey of maintenance policies of deteriorating systems. *European Journal of Operational Research*, 139(3), 469-489.
- (Zhang et al., 2011) Zhang, Z., Xu, H., Martin, R., & Liu, C. (2011). Inferential models for linear regression. *Pakistan Journal of Statistics and Operation Research*, 7(2-Sp).
- (Zio, 2006) Zio, E. (2016). Some Challenges and Opportunities in Reliability Engineering. *IEEE Transactions on Reliability*, 65(4), 1769-1782.

(Zio, 2013) Zio, E. (2013), Prognostics and Health Management of Industrial Equipment, Diagnostics and Prognostics of Engineering Systems: Methods and Techniques, Seifedine Kadry (Ed.), pp. 333-356.