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A novel fault detection system taking into account uncertainties in the reconstructed signals

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ABSTRACT

A typical fault detection (FD) system comprises: (1) a model that reconstructs the values of the measured signals in normal conditions, (2) a technique for the analysis of the differences (residuals) between the measured and reconstructed values, and (3) a decision strategy for defining when the monitored situation is to be detected as anomalous, i.e., reflecting a fault. Traditional techniques for this task, like threshold-based methods and the Sequential Probability Ratio Test (SPRT), show difficulties in setting their parameters and in providing information on the confidence of the FD system outcomes. In this context, the objective of the present work is to develop a novel, non-parametric, sequential decision strategy to decide whether the component is in normal or abnormal conditions that takes into account the quantified uncertainty on the reconstructions in the form of Prediction Intervals (PIs). The Auto-Associative Kernel Regression (AAKR) method is adopted to build the empirical model of signal reconstructions. The novel FD system has been tested using an artificial case study representing the monitoring of a component during typical start-up transients and it is validated using a real industrial case concerning 27 shut-down transients of a nuclear power plant (NPP) turbine. The obtained results show that the approach is able to guarantee low false and missing alarm rates and, hence, provide the decision makers with robust information for establishing whether a maintenance intervention is required or not.

1. Introduction

Over the last few decades, Condition Monitoring (CM) techniques have been strongly developed in terms of measurement devices, and data processing and management capabilities. These developments have encouraged industries like nuclear, oil and gas, automotive and chemical to apply Condition-Based Maintenance (CBM) (Jardine et al., 2006; Campos, 2009) for increasing system availability, reducing maintenance costs, minimizing unscheduled shutdowns and increasing safety (Thurston and Lebold, 2001; Yam et al., 2001; Miao et al., 2010).

A typical CBM scheme is shown in Fig. 1: a fault detection (FD) system continuously collects information from sensors mounted on the component of interest (Jardine et al., 2006; Ahmad and Kamaruddin, 2012) and delivers information on the health state (either normal or abnormal conditions) of the monitored component through an alarm system interface. On the basis of the received information, the decision maker decides whether it is necessary to perform a maintenance action or if it is possible to postpone it (Jardine et al., 2006).

In this work, we only focus on the FD system. This is typically made by an empirical reconstruction model and a decision tool that supports the decision maker. Several methods have been used with success to reconstruct values of the signals expected in normal conditions, for example Artificial Neural Networks (ANNs) (Ebron et al., 1990; Dong and McAvoy, 1994; Fantoni and Mazzola, 1996; Hines et al., 1997; Maki and Loparo, 1997; Xu et al., 1999; Hines and Davis, 2005) and Auto-Associative Kernel Regression (AAKR) (Hines and Garvey, 2006; Yang et al., 2006; Heo, 2008; Baraldi et al., 2012).

The decision tool typically analyzes the differences (residuals) between the measured and reconstructed values of the n measured signals in order to advice on the component health state (normal or abnormal conditions) (Fig. 2). If reconstructions are similar to measurements, then the component is recognized to be in normal conditions (nc) and no alarm is triggered, whereas if reconstructions are different from measurements, then abnormal conditions (ac) are detected and an alarm is triggered (Zhao et al., 2011; Di Maio et al., 2013).

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Notation and list of acronyms

CM	Condition Monitoring
CBM	Condition-Based Maintenance
FD	Fault Detection
ANN	Artificial Neural Networks
AAKR	Auto-Associative Kernel Regression
n	Number of measured signals
j	Index of the generic signal, $j = 1,\ldots,n$
nc	Normal Conditions
ac	Abnormal Conditions
γ	False alarm rate
β	Missing alarm rate
SPRT	Sequential Probability Ratio Test
PI	Prediction Interval
OS	Order Statistics
M	Length of the detection window
NPP	Nuclear Power Plant
N_p	Number of measurement times and/or representative turbine shaft speeds of each signal j, $j = 1,\ldots,n$
t_k	k-th time instant, $k = 1,\ldots,N_p$
$\varepsilon(t_k)$	Prediction error at the k-th time instant
$\vec{x}^{test}(t_k)$	Vector containing the test measurements of n signals at time t_k, $k = 1,\ldots,N_p$
$x^{test}(t_k, j)$	Measured value of signal j, $j = 1,\ldots,n$ at time t_k, $k = 1,\ldots,N_p$
$\vec{\widehat{x}}^{test}(t_k)$	Vector containing the reconstructed values of the test measurements of n signals at time t_k, $k = 1,\ldots,N_p$
$\widehat{x}^{test}(t_k,j)$	Reconstructed value of signal j, $j = 1,\ldots,n$ at time t_k, $k = 1,\ldots,N_p$
$\hat{x}^{lower}(t_k), \hat{x}^{upper}(t_k)$	Lower and upper bounds of PI at time t_k
$1 - \sigma$	Confidence level
$\alpha^{95percentile}(t_k)$	Sorted scale factor value at the k-th time instant for 95% confidence level, $k = 1,\ldots,N_p$
NV	Number of measurements/reconstructions in the validation set performed at time t_k after the beginning of the transient used to estimate the PIs
$var_k^{res}(\widehat{x}^{val}(t_k))$	Bias between NV measurements and their reconstructions at time t_k of signal j of the validation set
$var_k^{res}(\widehat{x}^{val}(t_k))$	Variance of NV reconstructions at time t_k of signal j of the validation set
t_1	1st time instant
N_{train}	Number of time series measurements in normal conditions of a training set
N	Component transients of signals measurements
i	i-th component transient, $i = 1,\ldots,N$
P_1	Probability that 1 signal j, $j = 1,\ldots,n$ is failed and detected for a given detection window of length M
P_n	Probability that at least one out of n signals are failed and detected for a given detection window of length M
P	Probability that a transient is failed and abnormal conditions are detected using $N_p - M + 1$ detection windows
$\gamma_{\max}$	Prefixed maximum limit of false alarm rate
$f_i(x(t, 1),\ldots,x(t, 4))$	i-th transient of four-dimensional ($n = 4$) signals with $N_p = 101$ time steps
$\vec{x}^{nc}_{i=1:4000}(t_k)$	Time evolutions in nc of the 4 signals in the 4000 transients at t_k, $k = 1,\ldots,N_p$ of the j-th signal (sigmoid behavior)
a, ζ and μ	Random parameters in arbitrary units used to construct transients in nc
$x_i^{nc}(t_k)$	Time evolutions in nc of the i-th transient at t_k, $k = 1,\ldots,N_p$ of the j-th signal (sigmoid behavior)
R	Number of operational zones of a component in normal conditions
h	Gaussian kernel bandwidth
t_f	Random failure time of a signal j, $j = 1,\ldots,n$ in a transient i, $i = 1,\ldots,N$
$x_i^{ac}(t_k)$	Time evolutions in ac of the i-th transient at t_k, $k = 1,\ldots,N_p$ of the j-th signal (different functional behavior)
a^* and μ^*	Random parameters in arbitrary unit used to construct transients in ac based on the signal value
$\overline{\overline{X}}$	Historical measurements performed at past time t_k, $k = 1,\ldots,N_{train}$
$x^{test}(t_k, 1)$	Test value of signal 1 measured at time t_k $k = 1,\ldots,N_p$
$x(t_k, j)$	Historical value of signal j measured at past time t_k, $k = 1,\ldots,N$ of $\overline{\overline{X}}$
$d^2(t_k)$	Euclidean distance between the current test measurements $\vec{x}^{test}(t,j)$ and the k-th observation of $\overline{\overline{X}}$, $x(t_k, j)$
$\mu(j)$ and $\sigma(j)$	Mean and the standard deviation of the j-th signal in $\overline{\overline{X}}$
$w(t_k)$	Similarity measures obtained by computing $d^2(t_k)$, $k = 1,\ldots,N$
$\alpha_i(t_k)$	Scale factor at the k-th time instant of the i-th validation transient, $i = 1,\ldots,NV$ of signal j
$e_i(t_k)$	Residual between the measured value of signal j and its reconstruction in the i-th validation transient, $i = 1,\ldots,NV$ at time t_k
$\widehat{x}_i^{val}(t_k)$	Reconstructed value of signal j at time t_k, $k = 1,\ldots,N_p$ in the i-th validation transient $i = 1,\ldots,NV$
$x^{test\text{-}normalized}(t, j)$	Normalized values of $x(t, j)$ at time t using $\mu(j)$ and $\sigma(j)$
$x_i^{val}(t_k)$	Value of signal j measured at time t_k, $k = 1,\ldots,N_p$ in the i-th validation transient $i = 1,\ldots,NV$
d	Outcome of the Durbin–Watson test

In threshold-based methods (Puig et al., 2008; Montes de Oca et al., 2012), the presence of abnormal conditions is detected when the residual values exceed a prefixed threshold. A practical difficulty is the setting of the threshold value itself: too high threshold values lead to high missing alarm rates (β), whereas too low values lead to high false alarm rates (γ) (Di Maio et al., 2013). Furthermore, threshold-based methods do not provide any information on the confidence that we should have in the FD system outcomes, such as expected missing and false alarm rates (Zhao et al., 2011). Contrarily, statistical methods which consider the residual as a random variable and analyze its statistical distribution, such as the Sequential Probability Ratio Test (SPRT) (Wald, 1947; Gross and Humenik, 1991; Schoonewelle et al., 1995; Hines and Garvey, 2006; Baraldi et al., 2010; Di Maio et al., 2013), typically allow obtaining the desired level of missing and false alarm rates. However, also they require the setting of some parameters such as those defining the expected statistical distributions of the residuals in abnormal conditions, which can be difficult in practical industrial applications (Emami-Naeini et al., 1988; Di Maio et al., 2013).

Independently from the choice of the reconstruction model and of the method adopted to analyze the residuals, the performance of the overall FD system is influenced by uncertainties which can cause false and missing alarms, and affect the decision on the necessity of performing a maintenance intervention (Helton, 1994; Zheng and Frey, 2005; Weber et al., 2007; Aven and Zio, 2012).

In this context, the objective of the present work is to develop a novel, non-parametric, sequential decision tool that takes into