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AN INTEGRATED APPROACH TO INDUSTRIAL GAS TURBINE DIAGNOSTICS AND RELIABILITY MONTORING

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ABSTRACT

Gas turbines are known to contribute to economic gains. But then, they are also covertly responsible for environmental loads. In the conventional approach, manufacturer supplied tool is used for condition monitoring. Drawbacks of such a tool include (i) the tool being designed for limited number and known types of faults, (ii) a tool specifically designed for experienced users, (iii) a tool featured by separate modules for monitoring and reliability, and (iv) a tool designed focusing on a particular system only. Meanwhile, the purpose of diagnostics and reliability are to enhance preventive maintenance. Hence, we suggest that they should be integrated to benefit from synergized use of the two aspects. Based on this argument, the purpose of this paper is to explore on the methods that integrate performance diagnostics with reliability monitoring. As it turned out, there is no specific method that addresses all the issues in fault diagnostics system design. The thermo-economic approach proved to be powerful in estimating performance changes and energy loss due to the presence of malfunctions. Nevertheless, this method cannot be used to address problems encountered by sensors outside the thermodynamic zone (e.g. vibration signal, lubrication condition etc.). Regarding reliability, there seems to be a gap in (i) defining states of the system, and (ii) in integrating reliability with diagnostics. There is also no performance indicator to evaluate efficacy of a diagnostic system as it relates to environmental load and economic gains. The paper includes additional remarks potentially useful for further research.

Keywords: gas turbine, fault diagnostics, reliability monitoring, fault detection.

INTRODUCTION

Gas turbines are widely used either as direct drive for are compressors or as a prime mover in electric power generation. They are preferred to steam turbines and reciprocating engines due to their fast starting characteristics and high power to weight ratio. With the current technology, a power as high as 340 MW can be generated by a single gas turbine. Efficiency up to 40% in open cycle and more than 60% in combined cycle configuration has been reported possible. In general, they are believed to be ideal for distributed power generation and for controlling the emission of greenhouse gases. However, gas turbines are highly specialized machines and hence they require advanced techniques to allow proactive maintenance. According to reports from different sources, the maintenance cost may reach up to 35% of the operating cost.

Typical design of a two-shaft gas turbine is shown in Figure-1. The core turbine drives the compressor while the power turbine is intended to induce rotational power on the generator shaft. In a separate design, the aero-derivative gas turbine may have a single shaft and the power from the tubine might be shared between the compressor and generator, in most cases 2/3 of the power used to drive the compressor.

Gas turbines may not stay at a performance level evisaged at the design stage, the reasons being (i) fouling in the air filter and compressor, (ii) aging of gas path components, (iii) excessive clearance due to rubbing, (iv) malfunctions, etc. The rate of deterioration might also be aggravated by local operating conditions and poor maintenance procedure. In relation to this, the idea that has been proposed and being pursued is to improvise the conventional maintenance procedure by incorporating advanced diagnostics, prognostis and reliability monitoring tools. An enhancement of the stated type is believed to ensure (i) safe and continuous operation, (ii) efficient use of the available energy, and (iii) controlled emission of greenhouse gases. Inline with this argument, it is the objective of the current paper to conducted a review and identify if integration of fault diagnostics and reliability monitoring has been attempted before.

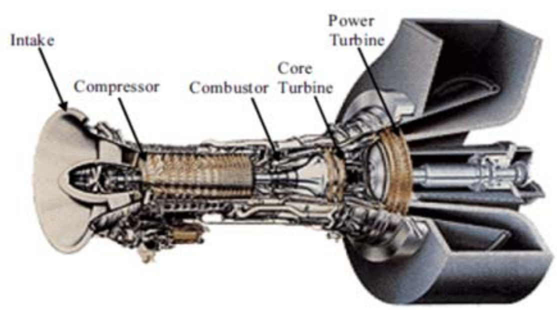

Figure-1. Typical two-shaft aero-derivative gas turbine with power turbine (Ogaji and Singh 2006).

A comprehensive review on performance analysis based diagnostics methods for both aero and industrial applications was reported in (Li 2002). Since then this particular work attracted 167 citations and it has been an excellent source for other similar review papers (Marinai, Probert *et al*. 2004, Bocaniala and Palade 2006, Lazzaretto and Toffolo 2006, Kong 2014). The current work, with the above mentioned objective, is opted to be considered as an extension of previous review papers. Apart from that, it is scoped to include (i) state of the art model identification

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methods, (ii) recent optimization techniques worth considering for diagnostics system design, and (iii) concepts lucking in multi-state reliability modeling and integration.

MODEL IDENTIFICATION

The design of a dynamic observer for fault diagnostics requires simple but reliable model. Assuming that the system dynamics is captured by a general nonlinear model that incorporates orthonormal basis filters, the output might be identified as

$$\begin{cases} \mathbf{g}(z,\boldsymbol{\xi}) = \dfrac{\sqrt{1-|\xi_j|^2}}{z-\xi_j}\displaystyle\prod_{i=1}^{j-1}\dfrac{1-\xi_i^* z}{z-\xi_i} z^{-d}, i=1,2,...,N \\ y(t) = f(\mathbf{g}(z,\boldsymbol{\xi});\boldsymbol{\theta}) + e(t) \end{cases} \quad (1)$$

Where, $\mathbf{g}(z,\boldsymbol{\xi}) = [g_0(z,\boldsymbol{\xi})u(t) \quad \cdots \quad g_n(z,\boldsymbol{\xi})u(t)]^T$; $\boldsymbol{\xi} = [\xi_1 \quad \xi_2 \quad \cdots \quad \xi_n]^T$ is vector of OBF poles with the condition that $\|g_i(z,\xi)\| = \|g_j(z,\xi)\| = 1$; d is the time delay; $\boldsymbol{\theta}$ is vector of model parameters; $e(t)$ is the modelling error which might be assumed identically and independently distributed or abounded in a certain range. Optimum values for $\boldsymbol{\theta}$ is to be decided by minimizing or maximizing a performance indicator (e.g. $V(\boldsymbol{\theta}) = \mathbf{e}^T(t)\mathbf{e}(t)/(2N)$) applying either derivative based or evolutionary algorithms. The other key step in the development of equation (1) is the selection of number of poles and their values. It is proved that for a system whose poles $\{p_j^0 : |p_j^0| < 1 \ for \ j = 1,2,...,n_0\}$ are known, the optimum selection for GOBF poles is governed by convergence rate, $\rho = \max_j \prod_{k=1}^{n} \left| \dfrac{p_j^0 - \xi_k}{1-\bar{\xi}_k p_j^0} \right|$. Equation (1) can be reduced to LTI or any other nonlinear models like ANN, Voltera and TSK.

$$CI(p) \approx \pm t_{\alpha/2, Nd-nx} \left\{ \hat{\sigma}_{ref}^2 \left[1 + \left(\mathbf{J}_k(\hat{\boldsymbol{\theta}})\right)^T \mathbf{H}_o \left(\mathbf{J}_k(\hat{\boldsymbol{\theta}})\right) \right] \right\}^{1/2} \quad (2)$$

Where, $\mathbf{J}(\hat{\boldsymbol{\theta}}) = \begin{bmatrix} \dfrac{\partial \Psi(\mathbf{u}(1),\hat{\boldsymbol{\theta}})}{\partial \theta_1} & \cdots & \dfrac{\partial \Psi(\mathbf{u}(1),\hat{\boldsymbol{\theta}})}{\partial \theta_{n\theta}} \\ \vdots & \ddots & \vdots \\ \dfrac{\partial \Psi(\mathbf{u}(N_d),\hat{\boldsymbol{\theta}})}{\partial \theta_1} & \cdots & \dfrac{\partial \Psi(\mathbf{u}(N_d),\hat{\boldsymbol{\theta}})}{\partial \theta_{n\theta}} \end{bmatrix}$

And, "o" stands for the training data; $\mathbf{H}_o(\hat{\boldsymbol{\theta}}) = \left[\left(\mathbf{J}(\hat{\boldsymbol{\theta}})\right)_o^T \left(\mathbf{J}(\hat{\boldsymbol{\theta}})\right)_o \right]^{-1}$, $t_{\alpha/2, N_d - n_\theta}$ is the percentage value of t – distribution that leaves a probability of $\alpha/2$ in the upper tail and $(1-\alpha/2)$ in the lower tail; $\mathbf{J}(\hat{\boldsymbol{\theta}}) \equiv \left[\left(\mathbf{J}_1(\hat{\boldsymbol{\theta}})\right)^T \quad \cdots \quad \left(\mathbf{J}_{N_d}(\hat{\boldsymbol{\theta}})\right)^T \right]^T$; $(N_d - n_\theta)$ is the degrees of freedom. Because σ^2 is unknown, the unbiased estimate, that is $\hat{\sigma}_{ref}^2$ is used in the calculation of CI.

$$\hat{\sigma}_{ref}^2 = \frac{1}{N_d - n_\theta} \sum_{k=1}^{N_d} \left[y^{(i)}(p) - \hat{y}^{(i)}(p) \right]^2 \quad (3)$$

OBFs are considered advantages for they allow using partial knowledge about the system dynamics to construct parsimonious models. However, OBFs have not be explored for diagnostics system design and also for applications intended specifically for gas turbines.

Basic structure of a fault diagnostics system

A fault in an industrial gas turbine can be of a controller fault $f_c(t)$, an actuator fault $f_a(t)$, a process fault $f_p(t)$ or a fault linked to the measurement sensors $f_u(t)$ or $f_y(t)$.

In relation to the process models, faults on inputs and outputs sensors, respectively, are often modelled either as additive type, $u(t) = u^*(t) + f_u(t)$, or multiplicative type, $f_u(t) = \delta u^*(t)$. Where the vector $f_u(t) = [f_{u1} \ f_{u2} \ ... \ f_{u,nu}]^T$ describes a specific fault signature and δ is the multiplier. Including the effect of measurement noise, $\tilde{u}(t)$ and $\tilde{y}(t)$, with the assumption that they are white, zero mean and uncorrelated Gaussian processes, faulty sensor signals can be modelled as

$$\begin{cases} u(t) = u^*(t) + \tilde{u}(t) + f_u(t) \\ y(t) = y^*(t) + \tilde{y}(t) + f_y(t) \end{cases} \quad (4)$$

Additive faults manifest themselves as offsets of sensors where as multiplicative faults appear as parameter changes within the process – e.g. fouling the compressor. Faults are also distinguished based on their time dependence as abrupt fault (stepwise), incipient fault (drift like), and intermittent fault.

A diagnostic system takes signals from input sensors, output sensors, and sensors for controller output (cf. Figure-2). Additional sensors might also be included to account for signals outside the control loop. Desirable characteristics of a diagnostics system and classification of diagnostics algorithms are discussed in a review paper by Venkatasubramanian *et al.* (Venkatasubramanian, Rengaswamy *et al.* 2003). In general, a diagnostics system is required to be reliable and flexible to respond to unknown cases. The challenge is to establish a framework that is capable of identifying the cause of problems based on limited combinations of upticks and downticks.

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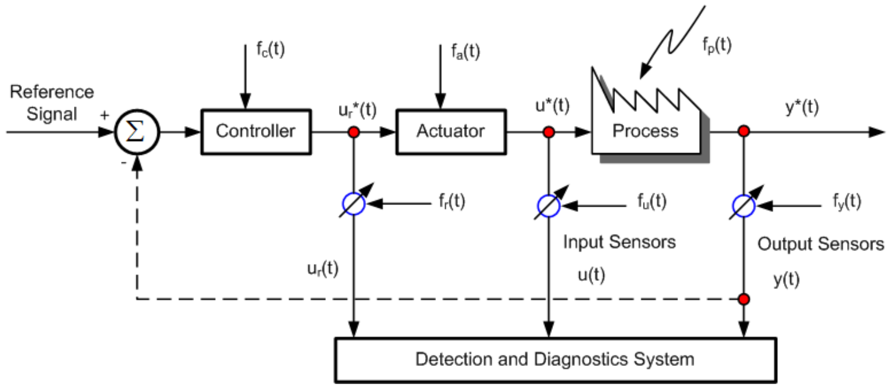

Figure-2. General structure for a fault diagnostics framework.

RESULT AND DISCUSSIONS

A number of studies have been reported on gas turbines performance diagnostics and reliability monitoring. The methods span expert systems to thermo-economic approachs. In the sequel, the most common diagnostics methods are reviewed.

Analytical methods

The methods in this group (observers, parity relations, parameter estimation, and Kalman filters) are considered as are the classical methods for fault diagnostics (Bocaniala, Palade *et al*. 2006). They are probably the oldest methods. All of them require mechanistic models, making them limited to systems having few numbers of inputs and outputs. Reported results show that these methods have been applied to steam generators (Koppen-Seliger, Kiupel *et al*. 1995), power plant boiler (Wang 1997), power plants (Simani, Fantuzzi *et al*. 1999), and thermal power plant (Alessandri, Coletta *et al*. 2003). One basic step of the method entails a model being simulated in parallel with the real system and residuals calculated as the difference between the model outputs and outputs from the plant. Later, the derangement is considered to detect and diagnose a problem. For gas turbines, it might be difficult to apply these methods attributed to the nonlinear relationship between system variables and the difficulty in developing a reliable first principle model. Perhaps the only exception is the method reported in (Simani 2005, Simani 2007). Simani has shown that a state observer or Kalman filter based diagnostic system can be developed replacing the state-space model by time series models like ARX and ARMAX. Selected literature on the use of classical diagnostics methods are listed in Table-1.

Table-1. Summary of classical diagnotics methods.

Method	Special features	Example reference
Dynamic Observer	Equation Error model used to form the state space model, Method used for residual generation	(Simani 2005, Simani 2007, Rahme and Meskin 2015)
Kalman Filter	Frishch scheme combined with EIV model are used to creat the state-space model, Kalman method is applied for residual generation Hybrid kalman filter design in the context of multi-model approach	(Simani 2005, Simani 2007, Ganguli 2012, Meskin, Naderi *et al.* 2013, Pourbabaee, Meskin *et al*. 2013)

Multivariate statistical process control

These methods are derived directly from measured process data. The first type, called PCA, is based on the mapping of covariance matrix of the data to a reduced dimension space applying Singular Value Decomposition (SVD). The fault detection is done applying Hotelling's T^2 and Q-statistic. The method has been applied to combined cycle gas turbines (Mina, Verde *et al*. 2008), and thermal plant (Ritchie and Flynn 2003). The second type, partial least squares (PLS), was also used in thermal plant (Ritchie and Flynn 2003), and combined cycle gas turbine power stations (Pan 2011). PCA relies on Gaussian error assumption which is not often the case. It also overlooks serial and self-correlations which makes it ineffective for systems whose behaviors change from with time (e.g. variable geometry compressors and turbines).

Computational intelligence

The methods in this group (artificial neural network, fuzzy systems, and nature or quantum inspired optimization algorithms) are generally considered nonlinear approaches. Either ANN or fuzzy systems can be used as residual generators or fault classifiers. Fuzzy systems allow incorporating expert's knowledge in the diagnostics system design. The fact that a single method could not fulfill all the design requirements also necessitated the combined use of ANN and fuzzy systems. Regarding the optimization algorithms (genetic algorithm,

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particle swarm optimization, bat algorithm, etc.), they have been applied to train models and decide on the number of inputs or model order. Sreedhar *et al.* (1995) and Vanini *et al.* (Sadough Vanini, Khorasani *et al.* 2014) investigated the use of neural networks and sliding observers for fault detection in a thermal power plant, and gas turbine, respectively. Simani, Fantuzzi *et al.* (1998) and Simani (2005) considered Kalman filters and neural networks for fault detection and diagnosis in industrial gas turbines. Leger, Garland *et al*.(1998), on the other hand, examined the feasibility of using neural networks combined with statistical control charts. Similar studies were reported in *(Bourassa 1999, Lu, Zhang et al*. 2001, Ogaji, Sampath *et al*. 2002). Regarding fuzzy systems, they have been used separately (Diao and M. Passino 2004, Ogaji, Marinai *et al*. 2005) and combined with ANN (2002). One drawback of CI techniques is that for large scale systems, they may not be able to provide better performance. There are suggestions that distributed fault detection and diagnosis system alleviate the drawback. One such design was reported in (Koppen-Seliger, Kiupel *et al.* 1995). Residuals from all subsystem were considered for fault isolation only. In the work of Heo and Lee (2006), it was suggested to use a multi-agent based fault diagnosis design that uses neural networks for modeling. A similar idea was also proposed by Arranz, Cruz *et al*. (2008).

Models based on the use of Computational Intelligence (CI) techniques have been found falling in one of the three basic structures, Figure-3. The first method is using either the neural network or the fuzzy system as a classification tool, Figure-3(a). In this case, all the input-output data are feed to the model and fault index delivered as an output. While this method works for simple systems with limited number of output features, it tends to be troublesome as the parameter size increases and if the process is featured by multiple operating conditions. In the second design, the intelligent model is still used as a classifier but the inputs are calculated by another algorithm, Figure-3(b). In this case, the numbers of inputs are limited to the number of states being monitored. A good example is the research work by Simani, Fantuzzi *et al*. (1998). The last approach is to use the intelligent system as modelling technique, Figure-3(c). In all the cases, curse of dimensionality seems an issue yet to be solved.

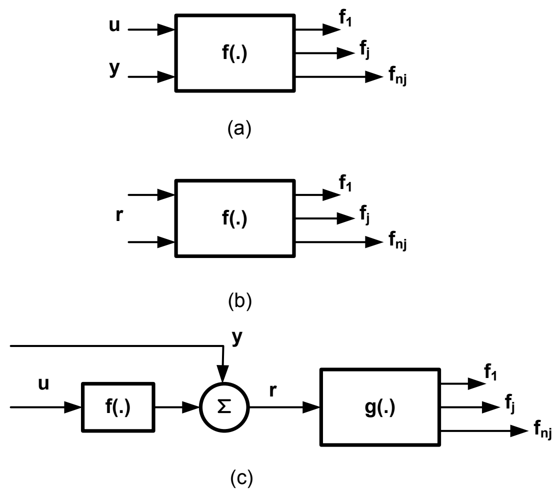

Figure-3. Basic application oriented structures of CI based FDD: (a) Direct use of measured Signals, (b) Models based on residuals, and (c) Models at two stages.

Expert system and causal models

These methods use structured knowledge as a critical element of the fault detection and diagnostics system. Predicate calculus, production- rules, frames, scripts or semantic networks are the common methods to build the knowledge base. In operation, the searching is carried out using forward chaining or backward chaining schemes. For a large searching space, however, depth-first and breadth-first searches may be considered. Applications of expert systems span coal fired power plant(Eddie and Moonis 1988), steam condenser(Stefanini, Cavanna *et al.* 1988), boiler feed water systems (Adamson 1990), and turbo-generators (McDonald, Stewart *et al*. 1991). Causal models, on the other hand, use causal relationships to associate a culprit for a particular fault. A typical example from this group is Symptom-Tree Model (STM). Causal models have been applied to steam boiler plant (Lee, Mo *et al*. 1997), and de-aerator system of a power plant (Ji, Wen-liang *et al*. 2005, Yong-Guang, Jian-Qiang *et al.* 2006). Drawbacks of an expert system are - (i) the difficulty to apply to large scale systems for they require large amount of effort, (ii) Often ad-hoc design, (iii) the need for huge amount of data, and (iv) requires and coding of expertise.

Thermo-economic approaches

Thermodynamic changes due to system malfunctions are better described by energy and thermo-economic approaches. As shown in the research work by Valero *et al*. (2004) and Lazzaretto *et al*. (Lazzaretto and Toffolo 2006) – many more papers are also available on the same idea –, a fault that could cause property change manifests itself as a rise in the fuel consumption or an increase in component irreversibility. Tracking the changes with respect to a reference value could lead to identification of the real cause, hence effective diagnostics. Over the years, several improvements have been made to the original formulation of the method. In terms of application, the case studies covered coal fired (Zhang, Chen *et al.* 2007) and combined cycle power plants (2004). The first weakness of this method is that, similar to the other methods, a reference model and actual operation data are required posing a challenge in applying it to systems with limited number of measured signals. It also fails to account for vibration, startup system and lube system signals. Sometimes, making a distinction between intrinsic and extrinsic faults are also challenging as they may both demonstrate similar kinds of symptoms. The idea thought to have overcome this problem is to combine the current method with other methods in the framework of multi-model design.

Multi-state reliability model

Equally researched in gas turbine based power plants is Multi-State Reliability prediction (Fazekas and Nagy 2010). Recently, Hagifam and Manbachi (2011) showed an MSS model constructed for a CHP plant. Subsystems like electricity generators, fuel distribution and heat generation were included. The states were defined using either ambient temperature data(Fazekas and Nagy 2010) or directly relying on the trend for electricity generated from a primary fuel. The limitation in the availability of long term data, however, has led to the need to focus on short-term reliability (Lisnianski, Elmakias *et al.* 2012). Even then, such studies cannot be performed based on steady state probabilities. This is to say that a different approach is needed to better characterize reliability of gas turbines, especially when they are intended to cater the power need for the peak hours.

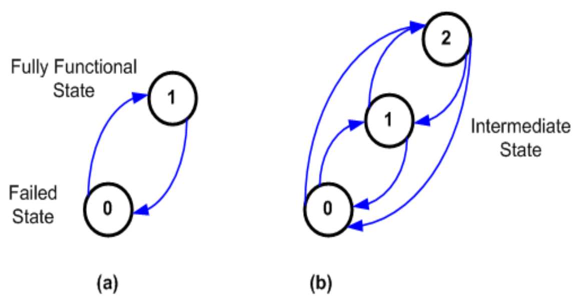

Figure-4. State definition for reliability modelling: (a) two-state, and (b) multi-state.

CONCLUSIONS

The purpose of this paper is to explore on the methods that integrate performance diagnostics and reliability monitoring. The following conclusions are drawn from the reported material:

- There is no specific method that addresses all the issues in fault diagnostics system design. And, this has led to the multi-agent or multi-model based design that uses hybrids of methods from different domains.
- The thermo-economic approach proved to be powerful in estimating performance changes and energy loss due to the presence of malfunctions. Nevertheless, this method cannot be used to address problems encountered in and by signals outside the thermodynamic zone (e.g. vibration signal, lubrication condition etc.).
- Orthonormal Bais Filters are reported to be ideal to for parsimonious models. This in the area of gas turbine diagnostics has not been reported yet. Perhaps integrating this with the likes of Kalman filter and computational intelligence method may ease the design difficult in multi-model approach.
- In reliability studies, there seems to be a gap in (i) defining states of the system, and (ii) in integrating reliability with diagnostics. There are also no performance indicators to evaluate efficacy of a diagnostic system as it relates to environmental load and economic gains.

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