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ORTHONORMAL BASIS FILTERS FOR GAS TURBINE FAULT DIAGNOSTICS SYTEM DESIGN: A REVIEW

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ABSTRACT

Gas turbines have become the dominant technology for power generation. They can be quickly assembled and put to service. They are convenient for engine exchange during system overhaul. The emission of NOx, SOx, CO, and particulates are also significantly law as compared to coal fired power plants. However, their maintenance cost is relatively high. The perceived best approach to reduce the cost is by using a proactive maintenance strategy in which a real-time diagnostics system plays a key role. The purpose of this paper is to review application of Orthonormal Basis Filters (OBFs) to fault detection and diagnostic systems design. The types of OBFs studied include Laguerre filters, Meixner filters, Kaurtz filters, Generalized OBF, and Markov-OBF. The combination of OBFs and computational intelligence methods (artificial neural network, fuzzy systems, and evolutionary optimization) are also highlighted. The review shows that, even though OBFs have been around for more than a decade, their application is limited to model identification only. As such, the only diagnostic problem revealed so far is that concentrating on stirred tank reactor. Therefore, to extend the use of OBFs to power plants, there needs to be further study in the context of power plants or specifically gas turbines.

Keywords: gas turbine, orthonormal basis filters, fault detecion, fault diagnostics.

INTRODUCTION

Gas turbines are widely used in oil and gas transmission either as direct drives for compressors or as prime movers for electric power generation. Single shaft, aero-derivative design of a gas turbine is shown in Figure 1. The thermodynamics in the axial compressor raises the pressure and temperature of the air. The compressed air and fuel mixture then undergo through an exothermic reaction in the combustion chamber leading to high temperature and pressure of the gas mixture. The hot gas then expands through the turbine resulting in rotational power on the turbine shaft. In an industrial gas turbine, the main shaft is connected to a generator shaft through a speed reduction gear box.

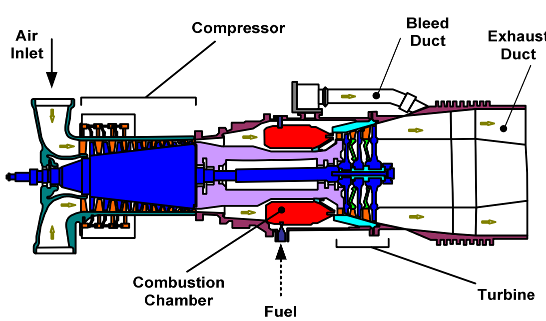

Figure-1. Single shaft gas turbine generator[1].

Gas turbines are equipped with variable geometry compressors, which allow a wider surge and stall margins during part load operations. In the starting mode and for speeds lower than about 65% of the design speed, the Inlet Guide Vanes (IGVs) and Variable Stator Vanes (VSVs) are at minimum opening position; at a speed of about 98%, they open fully with the opening starting at around 65% of design speed [1]. The latter region is identified as a variable geometry region where the IGVs and VSVs are manipulated to vary the air flow rate.

Meanwhile, the gas turbines used in cogeneration plants are expected to provide high temperature gas to the exhaust gas heat recovery steam generator. For loads higher than 50% of the rated value IGVs and VSVs are manipulated to vary the air flow rate in response to the load demand. The fuel flow rate, $\dot{m}_f$, is also varied to keep the turbine inlet temperature at the required set point. For a load lower than 50%, the gas turbine is on speed and load control. During this period the IGVs are fully open allowing maximum flow of air.

Real-time fault detection and diagnostics demand high fidelity models covering the controller and auxiliary systems. However, the way it is expected to operate, and unavailability of component performance maps and design information on the controller configuration makes it difficult to develop such a model. The fact of the matter is that it is not practical to provide performance maps for a variable geometry compressor, if the map is required for the whole operating region. Nevertheless, in the absence of performance maps and in a narrow operating zone, the compressor and turbine efficiencies might be assumed constant [2, 3], or empirical models might be tested [4, 5]. For instance, in Kakimoto and Baba [6], the pressure ratio in the compressor and turbine are described as a function of design pressure ratio and air flow rate while the efficiencies are assumed constant. In the work of Suzaki *et al*. [7], pressure ratio is defined as a function of rotational speed. Other alternative are to use either scaling method [8] or stage-stacking approach [9]. Regardless, the dynamic model development is hindered by missing inertial information, controller gains and time constants. Geometric parameters for the bleed valve, IGVs, and

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VSVs are rarely known. In such kind of situations, the authors believe that the designer has to resort to model identification methods which can be quickly applied if the historical data with good resolution is readily available.

The purpose of this paper is to review the application of Orthonormal Basis Filters (OBFs) in the design of fault detection and diagnostics system for gas turbines. The OBFs visited entail: Laguerre type, Meixner type, Kaurtz type, generalized form, and Markov design.

THE CONCEPT OF FAULT DIAGNOSTICS

A fault is said to be detected if the residual calculated between the actual output $y_i(p)$ and the predicted $\hat{y}_i(p)$ result is greater than the corresponding confidence interval for normal operating conditions. A general structure for FDD is shown in Figure-2.

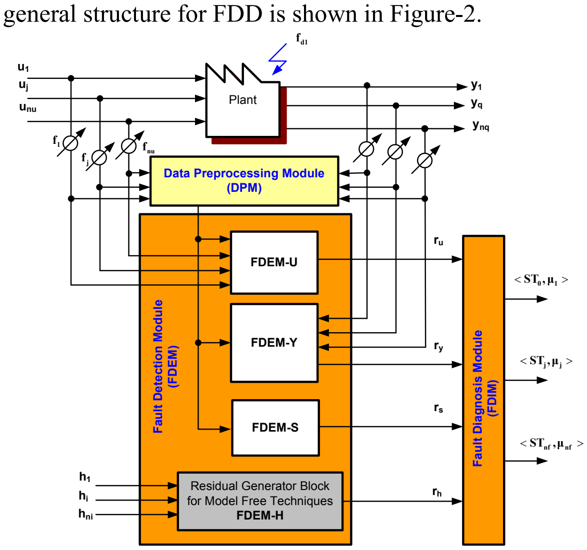

Figure-2. General structure of a fault diagnostics framework [1, 10].

ORTHONORMAL BASIS FILTERS

Two of the OBFs mostly used for model identification and control system design are Laguerre function and Kaurtz Function [11]. Two functions are said to be orthonormal if they are orthogonal to each other and if each function demonstrates Euclidian norm of unity; that is $\left\|\phi_i(q^{-1})\right\| = \left\|\phi_k(q^{-1})\right\| = 1$. In the frequency domain, the orthogonality condition between two functions $\phi_i(j\omega)$ and $\phi_k(j\omega)$ are satisfied if and only if

$$\left\langle \phi_i, \phi_k \right\rangle = \frac{1}{2\pi}\int_{-\infty}^{\infty} \phi_i(j\omega)\phi_k(j\omega)d\omega = \begin{cases} 0 \ if & i \neq k \\ 1 \ if & i = k \end{cases} \quad (1)$$

Where, $\langle .,. \rangle$ is inner product between functions $\phi_i(j\omega)$ and $\phi_k(j\omega)$, and q^{-1} is the shift operator.

Laguerre basis functions (LBF)[12]: is featured by a single pole ξ, with the condition that $\|\xi\| < 1$. LBF based model is appropriate for a system with a dominant first order model. The governing equation for *i*-th LBF filter is

$$\phi_i(q) = \sqrt{1-\xi^2}\,\frac{(1-\xi q)^{i-1}}{(q-\xi)^i}, \quad \|\xi\| < 1 \quad (2)$$

Meixner basis functions (MBF) [13]: These functions in z-transform are obtained from transformation of the discrete LBF by appropriate matrix. Similar to LBF, a single pole with the criteria of $\|\xi\| < 1$ is used to generate the basis. However, the additional term "β" that stands for order of generalization makes it suitable to accommodate delays in the system. It is shown in [14] that LBF and pulse functions are special cases of MBF; for $\beta = 0$, MBF reduces to LBF. With respect to LBF, MBF is less applied in model identification and control.

$$M_k^{(\beta)}(q) = \left(1-\xi^2\right)^{\beta+1/2}\left(\frac{q}{q-\xi}\right)^{\beta+1}\sum_{j=1}^{k} L_{k+1,j+1}^{(\beta)}\left(\frac{1-\xi q}{q-\xi}\right)^j \quad (3)$$

Kurtz basis function (KBF)[15]: KBF is the third type of OBF applied for model identification. Unlike the LBF, it involves two conjugate poles. For a system having dominant second order dynamics, models based on these functions have been found suitable. Laguerre and Kautz functions are special cases of generalized orthonormal basis functions.

$$\phi_{2i-1}(q) = \frac{\sqrt{(1-a^2)(1-b^2)}}{q^2 + a(b-1)q - b}\left[\frac{-bq^2 + a(b-1)q + 1}{q^2 + a(b-1)q - b}\right]^{i-1} \quad (4a)$$

$$\phi_{2i}(q) = \frac{\sqrt{(1-b^2)}(q-a)}{q^2 + a(b-1)q - b}\left[\frac{-bq^2 + a(b-1)q + 1}{q^2 + a(b-1)q - b}\right]^{i-1} \quad (4b)$$

Where, $-1 < a < 1$ and $-1 < b < 1$

Generalized orthonormal basis functions (GOBF): In this case a mix of different poles is used to define the bases. In 1995, Heuberger *et al.* [16] demonstrated the possibility of generating OBFs with repeated and fixed poles by assuming a minimum balanced State Space (SS) realization of inner functions with McMillan degrees $n_b > 0$. In 1997, Ninnes and Gustafson [17] came up with a unified approach by showing that the equation (6) makes up a complete orthogonal set with $\xi = \{\xi_j, j = 1,2,....\}$ signifying arbitrary poles inside the unit circle and in conjugate pairs. Latter in 2008, Toth [18] revealed that GOBF in fact resides to a bigger set of OBFs referred as Takanaki-Malmquist Functions (TMF). GOBFs have been chosen over the others for a system having scattered poles.

$$\phi_i(q) = \frac{\sqrt{1-\|\xi_i\|^2}}{(q-\xi_i)}\prod_{j=1}^{i}\left(\frac{1-\xi_i^* q}{q-\xi_j}\right), \quad \|\xi\| < 1 \quad (5)$$

Markov-OBF: As partially stated, one limitation of LBF, KBF and GOBF is that the time delay is not considered. After the contribution by Finn *et al*. [19], however, the time delay is included by putting some of the poles at the origin. The resulting orthogonal set is named Markov-OBF by Patwardhan and Shah [20], equation (7). Note that the three OBFs, including the pulse transfer functions, can be constructed from Markov-OBF. One drawback of using OBF is the pre-requirement on the dominant pole or poles of the system and time delay in case of using Markov-OBF.

$$\begin{cases} \phi_i(q) = q^i, \text{ for } i = 1,2,3,...,d \\ \phi_i(q) = \dfrac{\sqrt{1-\|\xi_i\|^2}}{(q-\xi_i)} \prod_{j=1}^{i} \left(\dfrac{1-\xi_i^* q}{q-\xi_j} \right), \text{ for } i > d \end{cases} \tag{6}$$

Construction of models using OBFs: The linear and nonlinear forms of OBF based modes takes the forms stated as equation (9) and equation (10), respectively.

$$y(p) = \sum_{i=0}^{n} \theta_i g_i(q,\boldsymbol{\xi}) + H(q,\theta)e(p) \tag{7}$$

$$y(p) = f(\mathbf{g}(q,\boldsymbol{\xi});\boldsymbol{\theta}) + e(p) \tag{8}$$

Where, $\mathbf{g}(q,\boldsymbol{\xi}) = \left[g_0(q,\boldsymbol{\xi})u(p) \quad \cdots \quad g_n(q,\boldsymbol{\xi})u(p) \right]^T$; $\boldsymbol{\xi} = [\xi_1 \quad \xi_2 \quad \cdots \quad \xi_n]^T$ is vector of OBF poles. For LTI models, the model parameters can be estimated applying the method of Least Squares (LS).

In terms of extent of studies, the most researched dynamic nonlinear model in the frame work of OBFs is the Volterra Systems [21-23]. In Volterra models, polynomial expansion of the input-output data is the foundation leading to the formulation of suitable models. A Volterra model has the advantage that it has a nonlinear structure, it is linear in parameters, and the model behaves stable for open-loop stable systems. However, Volterra models require more model parameters in order to achieve higher accuracy. In fact it is not common to see Volterra models with model orders higher than two because of the high computational burden. In the following, we would like to look at other alternative nonlinear models.

OBF- Artificial neural network: Even though Volterra models are well studied, recently the use of Artificial Neural Networks (ANN) and Fuzzy Systems (FS) in the frame work of OBF is introduced. In the research reported by Parker and Tumma [24], Wray and Green [25], Marmarelis and Zhao [26], Liu *et al*. [27], Alataris *et al*. [28], we find detail studies about the conditions under which Volterra models could be developed from neural network approach. It was shown by Back and Tsoi [29] that ANN incorporating Laguerre filters can approximate a Volterra model to a certain degree of accuracy. In the same year, 1996, Sentoni *et al*. [30] also explored the possibility of developing a nonlinear model from the use of ANN with single hidden layer and Laguerre filters. After a test on control of a binary distillation column, they have concluded that the model using the stated approach is indeed effective. Besides, they mentioned that time delay in the system can be considered by making adjustments on the input to the Laguerre filters. Convergence and generalization characteristics of OBF-ANN based models are studied by Balestrino *et al*. [31] and Abrahantes Vazquez *et al*. [32], respectively. In the work of Diwanji *et al*. [33], we see the application of Laguerre functions and ANN based nonlinear models to the design of a model predictive controller for a single spool gas turbine. The model is a result of direct adaptation of Weiner model structure [34]. The whole idea was to perform feasibility study and at the end they came to notice that the proposed approach is indeed better than NARMAX model, which is traditionally known problematic in terms of fixing the model structure and model orders. It is worth noting that, this is the only work we came across in the area of power plants.

OBF- fuzzy systems: Sbarbaro and Johansen [35] are, to our knowledge, the first to demonstrate a nonlinear model that incorporates Laguerre filters and at the same time possess the characteristics of fuzzy modeling. They used operating region dependent local approximations linked by weighting parameters that are reflections of fuzzy sets. In the same year, Nelles [36] proposed a similar model but the model was trained by LOLIMOT algorithm. Then latter in 1999, Oliveira *et al*.[37] reported a fuzzy relational model in the framework of OBFs. There are drawbacks regarding the models. Firstly, they assumed equally spaced cluster centres. Secondly, spread terms are set equal to half of the distance between two adjacent centres. Thirdly, they used a fixed pole of $\xi = 0.7$. None of these are realistic. In 2002, Campello and Amaral [38] published more general realization of the Oliveira's approach in which a state-space local model is assumed in the rules of the OBF-Fuzzy model. In their study, they used the model to design a controller for a polymerization reactor. In the following year, they also extended the approach to hierarchical fuzzy models [39]. While testing the possibility of training the models by LS and GA algorithms, they also studied the performance of the resulting models as part of a Model Predictive Control (MPC) system for an ethanol production plant [40].

Estimation for dominant pole: The other key step in the development of equation (8) is the selection of optimum number of poles and the corresponding values. It is proven that for a system having normalized poles $\left\{ p_j^0 : \left| p_j^0 \right| < 1 \;\; for \;\; j = 1,2,...,n_0 \right\}$, the optimum selection for GOBF poles is governed by convergence rate,

$$\rho = \max_j \prod_{k=1}^{n} \left| \frac{p_j^0 - \xi_k}{1 - \bar{\xi}_k p_j^0} \right| \tag{9}$$

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Estimation for model uncertainty:

The fault detector governed by the equation (1) requires an adaptive confidence interval which can be derived assuming linearization about the operating point. Assuming Taylor's first order approximation, the OBF model, can be stated as

$$y(p) = \Psi(\mathbf{u}(p);\hat{\boldsymbol{\theta}}) \approx \Psi(\mathbf{u}(p);\boldsymbol{\theta}^*) + \left(\mathbf{J}(\hat{\boldsymbol{\theta}})\right)^T \times (\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}^*) \quad (10)$$

Accordingly, it can be sown that

$$CI(p) \approx \pm t_{\alpha/2, Nd-nx} \left\{ \hat{\sigma}^2_{ref} \left[1 + \left(\mathbf{J}_k(\hat{\boldsymbol{\theta}})\right)^T \mathbf{H}_o \left(\mathbf{J}_k(\hat{\boldsymbol{\theta}})\right) \right] \right\}^{1/2} \quad (11)$$

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

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; $\mathbf{J}(\hat{\boldsymbol{\theta}}) \equiv \left[\left(\mathbf{J}_1(\hat{\boldsymbol{\theta}})\right)^T \cdots \left(\mathbf{J}_{N_d}(\hat{\boldsymbol{\theta}})\right)^T \right]^T$; $(N_d - n_\theta)$ is the degrees of freedom. Because σ^2 is unknown, the unbiased estimate, that is $\hat{\sigma}^2_{ref}$ is used in the calculation of CI.

$$\hat{\sigma}^2_{ref} = \frac{1}{N_d - n_\theta} \sum_{k=1}^{N_d} \left[y^{(i)}(p) - \hat{y}^{(i)}(p) \right]^2 \quad (12)$$

MODEL PERFORMANCE EVALUATION CRITERIA:

Suitability of the model can be assessed by using Akak's Information Criterion (AIC).

$$(AIC)^{(i)} = N_d \ln \left[\frac{1}{N_d} \sum_{k=1}^{N_d} \left[\varepsilon_i(p, \hat{\boldsymbol{\theta}}^{(i)}) \right]^2 \right] + 2n_\theta \quad (13)$$

Where, $n_\theta = (nu+1) \times nk$ is the number of estimated model parameters; $\hat{y}^{(i)}$ is the predicted output and $\varepsilon_i(p, \hat{\boldsymbol{\theta}}^{(i)}) = y^{(i)}(p) - \hat{y}^{(i)}(p)$. In addition to Equation (5), we have also adopted Variance Accounted For (VAF)

$$(VAF)^{(i)} = \left(1 - \frac{\mathrm{var}\left(y^{(i)} - \hat{y}^{(i)}\right)}{\mathrm{var}\left(y^{(i)}\right)} \right) \times 100\% \quad (14)$$

CONCLUSIONS

Developing a reliable and high fidelity model for a gas turbine is complicated by missing design point information and controller parameters. In a situation like that, it is generally advised to resort to time series models like AR groups (ARX, ARMAX, NARMAX, ARIMA, and Box Jenkins), Voltera series, ANN model or fuzzy approach. The present paper provided a brief review on the construction of such models in the context of OBFs (Laguerre, Meixner, Kaurtz, Generalized form, and Markov filters). Differences and similarities among OBFs have been highlighted. The main intention was to reveal that OBFs have been adopted in nonlinear model identifications and that they can be applied to power plant fault detection and diagnostics. Based on the presented summary, it can be concluded that

- OBFs are proven ideal to reduce the model order, and hence resulting in a parsimonious model. The first challenge, however, is that they require a decision on the optimum number of poles and model order.
- Even though good progress have been made in the construction of time series models with OBFs, the use of such kind of models of gas turbines seems lacking. The only reported paper is that limited to, model predictive control only.
- The confidence interval defined for time series models never included the effect of OBF poles.
- Among the five OBFs, LBF is the most widely used, with KBF comes second. Perhaps this is due to the single pole requirement in LBF application.

Future work will concentrate on the construction of fault detection and diagnostics system by using adaptive confidence intervals and OBFs.

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