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GAS TURBINE PERFORMANCE DIAGNOSTICS AND FAULT ISOLATION BASED ON MULTIDIMENSIONAL COMPLEX HEALTH VECTOR SPACE

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ABSTRACT

This study presents the method for detection and isolation of component faults and degradation modes in industrial gas turbine engine. Performance of gas turbine engines gradually deteriorate over the service life due to degradation of the gas path components such as compressor, combustor and turbines. These physical faults gradually evolve over a prolonged period of operation and lead to degradation of the performance parameters, such as efficiency and flow capacity of individual gas-path components.

Performance degradation, in turn, causes changes in the measurable engine parameters, such as temperature, pressure, rotational speed, and fuel flow rate. Traditionally these component degradation modes and faults in the engine have been detected by measuring the changes in these observable parameters through appropriate usage of signal processing and pattern recognition tools.

In this contribution model-based diagnostic approach has been applied, where measureable parameters have been used to estimate so-called engine health parameters, i.e. component efficiencies and flow capacities. Health parameter deviations from nominal conditions are subsequently used to obtain health indices and the best signature match is then used to identify likely component degradation modes and faults.

Performance diagnostic and fault isolation process is based on multidimensional complex health vector space which contains generated health indices, i.e. component capacity and efficiency indices for different gas turbine components. Simulated gas turbine degradation modes have been diagnosed and isolated by comparing gas turbine health vector against bank of fault signatures for different gas-path components.

NOMENCLATURE

Variables

I health index
Γ capacity
η efficiency
D discriminant
H, χ health vector
E, ε fault vector
Ψ isolation index
W weight factor
e fault signature

Subscripts \ Superscripts

cmp component
n number of components
flt fault
k number of faults
ort orthogonality test
col collinearity test
dir directionality test
pmt plane magnitude test
smt space magnitude test

INTRODUCTION

The physical faults in a gas turbine engine include problems such as erosion, corrosion, fouling, foreign object damage (FOD), worn seals, burned or bowed blades, etc. These physical faults can occur individually or in combination and cause changes in performance characteristics of the different gas turbine components. These changes in the performance of the gas turbine components result in changes in the gas path measurement parameters, which are typically used for diagnostic purposes (Li, 2002).

Current degradation monitoring, fault detection and isolation tools vary widely in their complexity and applications and are primarily built upon both model-based and sensor-based analyses. Model based techniques exploit gas turbine models to estimate engine internal conditions, enabling in that way implementation of various diagnostic methods. Model-based information is the foundation of many diagnostics and control strategies, ranging from simple thresholding to sophisticated pattern recognition methods.

Numerous diagnostic algorithms have been developed to estimate engine condition and identify faults from the health signals using weighted least squares (Doel, 1994, 2002), Kalman filter (Urban and Volponi, 1992) and neural networks (Zedda and Singh, 2000, Lu et al., 2001, Volponi et al., 2003). More recently various techniques such as Bayesian belief networks (Lee et al., 2010), genetic algorithms (Sampath et al., 2003), polynomial functions (Cerri et al., 2011) and different hybrid methods (Volponi et al., 2005, 2007) have been explored for use in performance tracking and fault diagnosis.

The developed model-based diagnostic approach is based on the measureable gas turbine parameters which have been used to estimate so-called engine health parameters, i.e. efficiencies and capacities for different gas-path components. On the another hand, devised diagnostic method employs dynamic gas turbine model as a performance tracking tool for generation of predicted health parameters for selected engine components. Performance tracking method is based on the observer which was constructed using non-linear dynamic gas turbine model with model tuner. The health parameters deduced by the performance estimation tool were then introduced into a dynamic model via model tuner which was designed using Kalman filtering technique.

The residual deviations between predicted and estimated component losses and flow capacities are subsequently used to generate health indices and the best signature match is then employed to identify likely component degradation modes and faults.

MODEL STRUCTURE

The generic simulation tool "GasTurboLib" (Panov, 2009), was used to build non-linear model of twin-shaft gas turbine engine. Created dynamic model is a physics based and has component-oriented architecture, where each module represents individual component. Different engine configurations can be created using this generic simulation tool and these models can be used for real-time simulations.

The component models include conservation of mechanical energy for engine shafts, heat-soaking effects for metal parts, and conservation of thermodynamic energy within different gas volumes in the engine. The detailed dynamics model of gas turbine engine can be expressed with a system of non-linear differential equations in state space:

$$\dot{x} = f_x(x,u,v) \tag{1.1}$$

$$y = g_y(x,u,v) \tag{1.2}$$

where x is state coordinate vector, u is control vector, v is vector of operating conditions, and vector y contains measurable y_m and non-measurable parameters y_n.

As a gas turbine engine undergoes internal changes, these changes may be manifested in performance degradation. To account for this degradation original state and output equation could be augmented with an additional vector $\boldsymbol{h}$ containing health parameters:

$$\dot{x} = f_x(x,h,u,v) \tag{2.1}$$

$$y = g_y(x,h,u,v) \tag{2.2}$$

The vector $\boldsymbol{h}$ contains health parameters that indicate the engine health conditions. Health parameters are usually represented by efficiencies and flow capacities of the engine components. As they deviate from their normal health conditions, the performance delivered by each component degrades, and this can be recognized as a shift in component characteristics (Razak, 2007). Generally speaking, we can recognize two main reasons for engine performance deviation: ***engine-to-engine variations*** and ***engine deterioration***.

Since the gas turbine model represents "nominal" engine, it must be adapted to the performance of the real engine as it deviates from nominal baseline with time. To address this problem, tuning of the engine model can be performed so that model aligns to the actual engine being monitored using ***model based tracking*** approach (Fig. 1.).

In this study performance tracking was achieved by the two step process. The gas turbine health parameters are estimated by performance estimation tool, and then subsequently they are introduced into dynamic real-time model via model tuner (Panov, 2014).

Selected set of health parameters is obtained using estimation function:

$$z = g_z(y_m) \tag{3}$$

which is based on the performance model that utilizes the mass and thermodynamic energy balances.

Vector z contains estimated health parameters, component capacities and efficiencies, which are obtained from available engine instrumentation readings.

Vector of measured engine parameters y_m, beside temperature and pressure measurements at different engine stations, contains also speed and acceleration rate of rotating shafts, addressing in that way dynamic behaviour of monitored health parameters.

To secure numerical stability of the dynamic gas turbine model, tuning of the health parameters must be done with care. Applied model tuning process based on Kalman filtering technique generates smooth tuners, enabling in that way robust execution of real-time dynamic models (Panov, 2011).

The estimated health parameters z based on the measurements from engine instrumentation are compared with smoothed estimates of health variables $\hat{z}$, where resulting vector is then used for generation of model tuners ξ and correction of the state variables $\boldsymbol{x}$. Therefore above gas turbine dynamic model, expanded with model tuner takes following form:

$$\begin{bmatrix} \dot{\hat{x}} \\ \dot{\hat{\xi}} \end{bmatrix} = \begin{bmatrix} f_x(\hat{x},\hat{h},u,v,\hat{\xi}) \\ f_\xi(\hat{\xi},\hat{h}) \end{bmatrix} + \begin{bmatrix} 0 \\ K(z-\hat{z}) \end{bmatrix} \tag{4.1}$$

$$\hat{y} = g_y(\hat{x},\hat{h},u,v,\hat{\xi}) \tag{4.2}$$

where function K represents tuner gain, which can be considered as a design parameter that is specified by user, and vectors $\hat{x}$ and $\hat{h}$ represent the estimates of the state variables and predicted health parameters, respectively. Gain matrix K is designed using linear quadratic theory to form Kalman filter gain matrix.

Model-based diagnostics employs engine models tuned to match the observed engine state in the same manner as ***model-based performance tracking*** (Panov, 2013). The residual deviations between predicted and estimated health parameters are modelled, again usually as variations in component losses and flow capacity, and the best match is used to identify likely component degradation modes and faults (Fig. 1.).

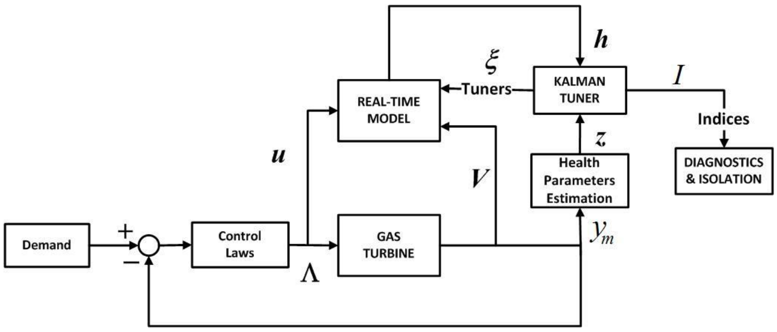


Fig. 1. Model Based Diagnostics & Isolation

A number of causes can result in gas turbine performance deterioration. Goal of diagnostics is to attempt to detect one or more of these causes that are responsible for the deterioration of engine performance. Usually this detection process is based on monitoring of so-called “health indices”.

Health indices are means of determining the deteriorated component characteristics. They represent the percentage change in component characteristics usually due to component faults or gradual degradation. Typically two health indices can be defined for any component and they correspond to the capacity and efficiency index:

$$I_\Gamma = 100 \times \frac{\Gamma^\xi - \Gamma^h}{\Gamma^h} = 100 \times \frac{\Delta\Gamma}{\Gamma^h} \tag{5.1}$$

$$I_\eta = 100 \times \frac{\eta^\xi - \eta^h}{\eta^h} = 100 \times \frac{\Delta\eta}{\eta^h} \tag{5.2}$$

DIAGNOSTICS

Fault detection and isolation play a critical role in enhancing the engine reliability and reducing operating cost of gas turbine engines. Engine component degradation and faults may occur in various degrees of severity and at various locations, and numerous scenarios are possible. We can distinguish three general classes of engine faults, namely, ***sensor***, ***actuator*** and gas turbine ***component faults***. This contribution considers only detection and isolation of the gas path component faults and degradation modes. Performance diagnostic and fault isolation process is based on multidimensional complex heath vector space which contains health indices, i.e. component capacity and efficiency indices for different gas turbine components.

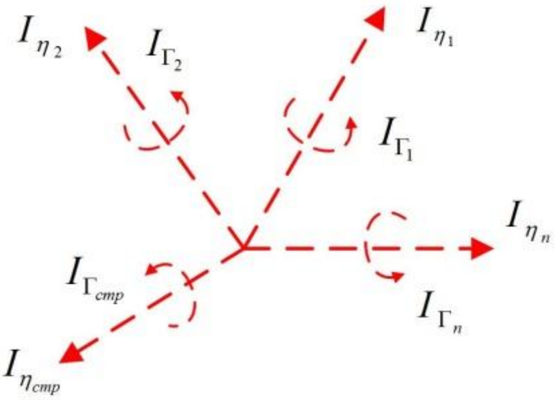
Health vector

Gas turbine ***health vector*** is defined in n-dimensional Euclidean space $\Re^n$:

$$\mathrm{H} = \begin{bmatrix} I_1 \\ \vdots \\ I_n \end{bmatrix} \tag{6}$$

where number of dimensions corresponds to the number of engine components under consideration. Scalars I_i are complex numbers constructed using component indices, where real part is represented by efficiency index, and complex part by capacity index of the corresponding component.

$$\mathrm{H} = \begin{bmatrix} \pm I_{\eta_1} \pm I_{\Gamma_1} i \\ \vdots \\ \pm I_{\eta_n} \pm I_{\Gamma_n} i \end{bmatrix} \tag{7}$$



Health vector of specific engine component in n-dimensional space is defined as follows:

$$\mathrm{H}_{cmp} = \begin{bmatrix} 0 \\ \vdots \\ I_{cmp} \\ \vdots \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ \pm I_{\eta_{cmp}} \pm I_{\Gamma_{cmp}} i \\ \vdots \\ 0 \end{bmatrix} \tag{8}$$

where $cmp = 1,\dots,n$.

Component health vector in complex plane is represented with corresponding element in the gas turbine health vector, i.e. with real and imaginary part of component efficiency and capacity respectively.

$$\chi_{cmp} = \begin{bmatrix} \pm I_{\eta_{cmp}} & \pm I_{\Gamma_{cmp}} i \end{bmatrix} \tag{9}$$

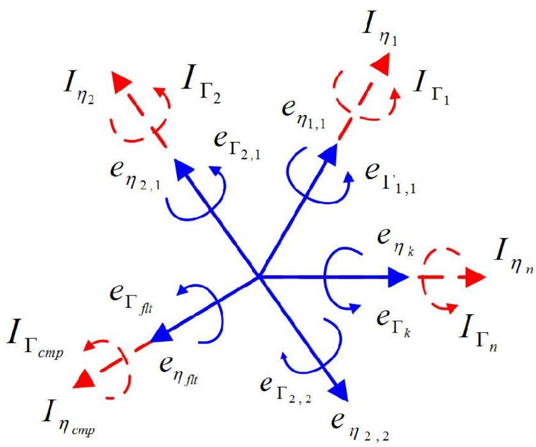
Fault vector - signatures

Gas turbine ***fault vector***, similarly as a health vector is defined in n-dimensional space $\Re^n$:

$$\mathrm{E} = \begin{bmatrix} e_1 \\ \vdots \\ e_n \end{bmatrix} \tag{10}$$

where number of dimensions corresponds to the number of engine components for which diagnostic process is applied. Each engine component could exhibit different faults or degradation modes, and they are described with corresponding component health indices, i.e. efficiency and capacity index. Therefore fault vector, i.e. signature of particular component fault in n-dimensional space is described with complex element in n-dimensional vector:

$$\mathrm{E}_{flt} = \begin{bmatrix} 0 \\ \vdots \\ \pm e_{\eta_{flt}} \pm e_{\Gamma_{flt}} i \\ \vdots \\ 0 \end{bmatrix} \tag{11}$$



where $flt = 1,\dots,k$ and $k \geq n$.

Number of faults is equal or greater of number of engine components, because same engine component can suffer from different faults or degradation modes. Corresponding fault vector in complex plane is represented with complex vector, containing component efficiency and capacity signatures as real and complex part respectively:

$$\varepsilon_{flt} = \left\lfloor \pm e_{\eta_{flt}} \quad \pm e_{\Gamma_{flt}} i \right\rfloor \tag{12}$$

Classification discriminants

In reality there is a very wide range of different engine faults. Classification of faults is usually based on different criteria, and generally they can be divided into ***single*** and ***multiple faults***. It would be ideal to address all these faults (sensor, actuator and component faults) under one unified diagnostic framework, and several researchers have investigated the development of such diagnostic framework (Dewallef and Leonard, 2003, Volponi et al., 2003, Surrender and Ganguli, 2004).

In practice, for the analysis of the engine degradation, engine faults have to be divided into the limited number of ***fault classes***. Typically it is considered that every fault class corresponds to particular engine component.

To isolate the diagnostic information, a classifier is added to model-based detection process, and numerous techniques have been applied in the past as a ***classification engines***. In presented application the simulated gas turbine degradation modes have been diagnosed and isolated using pattern-recognition approach, by comparing gas turbine health vector against bank of fault signatures for different gas-path components.

In order to classify the fault signatures correctly according to the corresponding gas turbine conditions, several discriminant test functions were selected (Aretakis and Mathioudakis, 1998). Three discriminant function are applied in complex vector space (orthogonality, colinearity and magnitude test), and additional two tests are applied in complex vector plane (directionality and magnitude test).

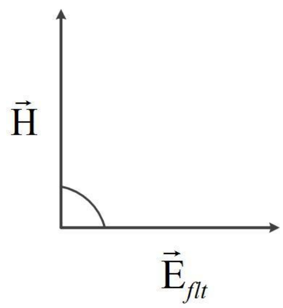
Orthogonality test – complex space

Orthogonality test is based on the vector dot product in n-dimensional $\Re^n$ complex vector space:

$$D_{flt}^{ort,m} = H \bullet E_m \text{ and } flt \neq m \tag{13}$$

where $flt = 1,...,k$; $m = 1,...,k$ and k - number of faults.

$$D_{flt}^{ort,m} = \begin{bmatrix} \pm I_{\eta_1} \pm I_{\Gamma_1} i \\ \vdots \\ \vdots \\ \vdots \\ \pm I_{\eta_n} \pm I_{\Gamma_n} i \end{bmatrix} \bullet \begin{bmatrix} 0 \\ \vdots \\ \pm e_{\eta_{flt}} \pm e_{\Gamma_{flt}} i \\ \vdots \\ 0 \end{bmatrix} \tag{14}$$



In case that angle between gas turbine health vector and fault vector, is right angle:

$$\alpha = 90^o \Rightarrow \cos(\alpha) = 0 \tag{15}$$

vectors are said to be mutually orthogonal and discriminant based on vector dot product is equal to zero:

$$D_{flt}^{ort,m} = \mathrm{H} \bullet \mathrm{E}_m = \|H\| \|\mathrm{E}_m\| \cos(\alpha) = 0 \tag{16}$$

Collinearity test – complex space

Wedge product or Grassmann product of vectors in n-dimensional vector space $\Re^n$ is used to define ***Collinearity test***:

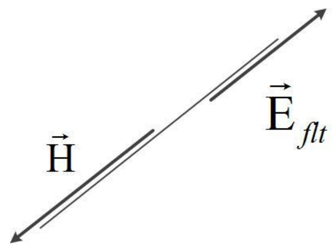
$$D_{flt}^{col} = \left\| H \wedge E_{flt} \right\| \qquad (17)$$

Grassmann product is generalization of vector cross product in 3-dimensional vector space $\Re^3$, which is used to describe collinear vectors. Two vectors are said to be collinear if they are parallel, i.e. angle between vectors is defined as follows:

$$\beta = 0, \pi, 2\pi, \ldots \Rightarrow \sin(\beta) = 0 \qquad (18)$$

Wedge product of gas turbine health vector and fault vector, which are collinear returns zero vector:

$$\mathrm{H} \wedge \mathrm{E}_{flt} = \begin{bmatrix} \pm I_{\eta_1} \pm I_{\Gamma_1} i \\ \vdots \\ \vdots \\ \vdots \\ \pm I_{\eta_n} \pm I_{\Gamma_n} i \end{bmatrix} \wedge \begin{bmatrix} 0 \\ \vdots \\ \pm e_{\eta_{flt}} \pm e_{\Gamma_{flt}} i \\ \vdots \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \qquad (19)$$



and hence discriminant based on the magnitude of the wedge product is equal to zero:

$$D_{flt}^{col} = \left\| \mathrm{H} \times \mathrm{E}_{flt} \right\| = \left\| \mathrm{H} \right\| \left\| \mathrm{E}_{flt} \right\| \sin(\beta) = 0 \qquad (20)$$

Directionality test – complex plane

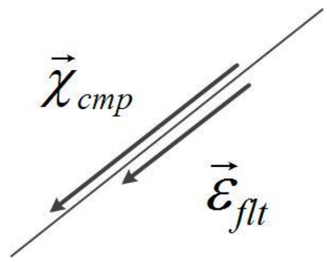
Dot product of component health vector and fault vector in the complex plane:

$$\chi_{cmp} \bullet \varepsilon_{flt} = \left\| \chi_{cmp} \right\| \left\| \varepsilon_{flt} \right\| \cos(\theta) \qquad (21)$$

where $cmp = 1, \ldots, n$ and n - number of components.

is used for definition of the ***Directionality test*** in the complex plane:

$$D_{flt}^{dir} = \arccos\left(\frac{\left(\chi_{cmp} \bullet \varepsilon_{flt} \right)}{\left\| \chi_{cmp} \right\| \left\| \varepsilon_{flt} \right\|} \right) \qquad (22)$$



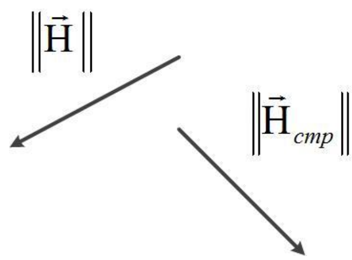
In case that component health vector and fault vector have same direction in the complex plane, angle between them is equal to zero ($\theta = 0$), and hence corresponding discriminant has the same value:

$$D_{flt}^{dir} = \theta = 0 \qquad (23)$$

Magnitude test – complex space

Gas turbine and component health vector magnitudes are used for definition of ***Magnitude test in complex space***:

$$D_{flt}^{smt} = \left\| \left\| H_{cmp} \right\| - \left\| H \right\| \right\| \qquad (24)$$



In case that Euclidian length of gas turbine health vector:

$$\left\| \mathrm{H} \right\| = \left(\sum_{i=1}^{n} \left| I_i \right|^2 \right)^{1/2} \qquad (25)$$

is equal to Euclidian length of component health vector:

$$\left\| H_{cmp} \right\| = \sqrt{I_{cmp} \cdot I_{cmp}} \qquad (26)$$

discriminant of magnitude test in n-dimensional complex vector space is equal to zero:

$$D_{flt}^{smt} = \left\| \left\| H_{cmp} \right\| - \left\| H \right\| \right\| = 0 \qquad (27)$$

<u>Magnitude test – complex plane</u>

Magnitude test in complex plane is represented with difference between magnitude of component health vector and fault vector in complex plane:

$$D_{flt}^{pmt} = \left\| \left\| \chi_{cmp} \right\| - \left\| \varepsilon_{flt} \right\| \right\| \qquad (28)$$

When Euclidian length of component health vector:

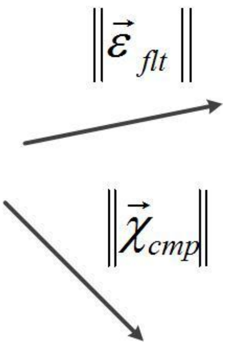
$$\left\| \chi_{cmp} \right\| = \sqrt{\chi_{cmp} \cdot \chi_{cmp}} \qquad (29)$$

is equal to length of fault vector in complex plane:

$$\left\| \varepsilon_{flt} \right\| = \sqrt{\varepsilon_{flt} \cdot \varepsilon_{flt}} \qquad (30)$$

corresponding discriminant has value of zero:

$$D_{flt}^{pmt} = \left\| \left\| \chi_{cmp} \right\| - \left\| \varepsilon_{flt} \right\| \right\| = 0 \qquad (31)$$



ISOLATION – DISCRIMINANT VECTOR, ISOLATION INDEX, WEIGHT FACTOR

Once diagnostic process is completed, which consists of determination of selected discriminants, isolation process can be applied. Isolation process is based on fault isolation index, which is derived using norm of discriminant vectors and probabilistic weight factor.

For each considered fault, discriminant vector is constructed using previously determined corresponding discriminants:

$$D_{flt} = \left[\left[D_{flt}^{ort,1}, \ldots, D_{flt}^{ort,m} \right], D_{flt}^{col}, D_{flt}^{dir}, D_{flt}^{pmt}, D_{flt}^{smt} \right] = \left[D_{flt,1}, \ldots, D_{flt,d} \right] \qquad (32)$$

where d is number of selected discriminants.

Sorting norms of discriminant vectors for all considered faults:

$$N_{flt} = \left\| D_{flt} \right\| = \left(\sum_{i=1}^{d} \left| D_{flt,i} \right|^2 \right)^{1/2} \text{ where } flt = 1, \ldots, k \text{ and } k \text{ - number of faults} \qquad (33)$$

puts them in order where the most likely degradation mode \ fault corresponds to min value: $\min\{N_1, \ldots, N_k\}$

Norms now can be used to determine fault isolation indices (Mucino and Li, 2005) for all the examined faults according to the following equation:

$$\Psi_{flt} = 100 \cdot W_{flt} \cdot \left(1 - N_{flt} \right) \qquad (34)$$

where W_{flt} is fault weight factor defined as arithmetic average of weight factors for component fault efficiency and capacity:

$$W_{flt} = \frac{1}{2} \left(W_{\eta_{flt}} + W_{\Gamma_{flt}} \right) \qquad (35)$$

Component fault weight factors represent probability of having a particular component fault and they are defined as follows:

- Weight factor for component fault efficiency

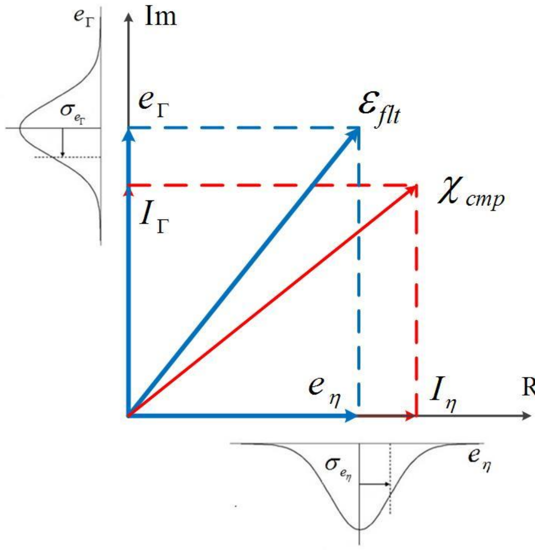
$$W_{\eta_{flt}} = e^{-\frac{\left(I_{\eta_{cmp}} - e_{\eta_{flt}}\right)^2}{2\sigma^2_{\eta_{flt}}}} \quad (36)$$

where $\sigma_{\eta_{flt}}$ is standard deviation for component fault efficiency,

- Weight factor for component fault capacity

$$W_{\Gamma_{flt}} = e^{-\frac{\left(I_{\Gamma_{cmp}} - e_{\Gamma_{flt}}\right)^2}{2\sigma^2_{\Gamma_{flt}}}} \quad (37)$$

where $\sigma_{\Gamma_{flt}}$ is standard deviation for component fault capacity.



In order to classify an examined signature to a particular fault, which is based on the corresponding fault vector, one can calculate fault isolation indices for all considered fault/degradation modes. The isolation process is then completed by classifying the signature to the mode that corresponds to the maximum isolation index (the better similarity the closer to 100% value).

NUMERICAL SIMULATION

For numerical simulation of abrupt and progressive degradation of different engine components (Kurz and Brun, 2000), two engine models have been created, where one model simulated “real” engine and second represented on-line engine model with tracking filter and diagnostic agent. Noise and biases of the engine instrumentation are implemented into the model representing “real” engine to introduce model-plant mismatch.

Dynamic model of industrial twin-shaft gas turbine engine has been used in this study. Available engine instrumentation for this gas turbine is listed in table Tab. 1. Engine health parameters derived by devised performance estimation tool using available engine instrumentation are listed in table Tab. 2.

Tab.1. Gas turbine measurements

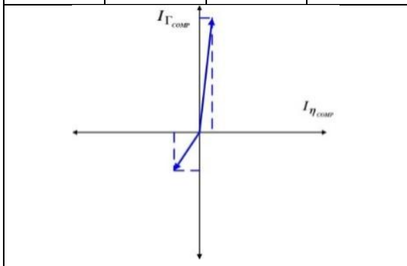
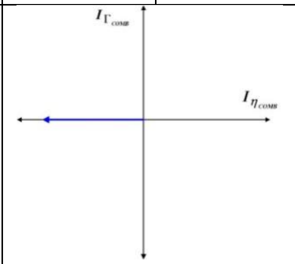
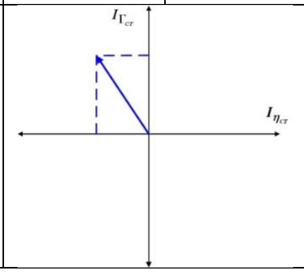
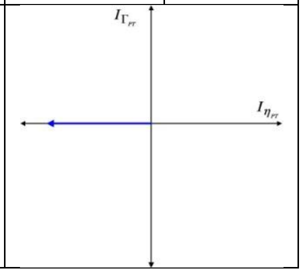
No	Description	Sensor Type	Notation
1	Compressor inlet	Pressure	P_{in}
2	Compressor inlet	Temperature	T_{in}
3	Compressor delivery	Pressure	P_{cd}
4	Compressor delivery	Temperature	T_{cd}
5	Inter-duct	Pressure	P_{id}
6	Inter-duct	Temperature	T_{id}
7	Exhaust	Temperature	T_{ex}
8	Gas generator shaft	Speed	n_{gg}
9	Power turbine shaft	Speed	n_{pt}

Tab.2. Health parameters for 4 gas turbine components

No	Component	Parameter	Notation
1	Compressor	Efficiency	η_{comp}
2	Compressor	Capacity	Γ_{comp}
3	Combustor	Efficiency	η_{comb}
4	Compressor turbine	Efficiency	η_{ct}
5	Compressor turbine	Capacity	Γ_{ct}
6	Power turbine	Efficiency	η_{pt}

Based on the deduced engine health parameters, corresponding health indices have been determined, and compered against bank of fault signatures for different gas-path components listed in Tab .3.

Tab. 3. Fault vectors for 5 fault signatures

FAULT CLASSES									
Compressor				**Combustor**		**Compressor Turbine**		**Power Turbine**	
Compressor Fouling		**VGV Offset**		**Combustor Degradation**		**CT Erosion**		**PT Tip Rub**	
$I_{\eta_{comp}}$	$I_{\Gamma_{comp}}$	$I_{\eta_{comp}}$	$I_{\Gamma_{comp}}$	$I_{\eta_{comb}}$	$I_{\Gamma_{comb}}$	$I_{\eta_{ct}}$	$I_{\Gamma_{ct}}$	$I_{\eta_{pt}}$	$I_{\Gamma_{pt}}$
-2%	-3%	+1%	+9%	-4%	-	-2%	+3%	-4%	-
									

Simulated gas turbine degradation modes have been diagnosed and isolated by classification engine based on several discriminant test functions listed in table Tab. 4.

Tab. 4. Clasification discriminants for 4-dimensional health vector and 5 fault classes

FAULT CLASSES				
Compressor		**Combustor**	**Compressor Turbine**	**Power Turbine**
Compressor Fouling	***VGV Offset***	***Combustor Degradation***	***CT Erosion***	***PT Tip Rub***
ORTHOGONALITY TEST - DISCRIMINANTS				
$D_{CMF}^{ort1}, D_{CMF}^{ort2}, D_{CMF}^{ort3}, D_{CMF}^{ort4}$	$D_{CMV}^{ort1}, D_{CMV}^{ort2}, D_{CMV}^{ort3}, D_{CMV}^{ort4}$	$D_{CMB}^{ort1}, D_{CMB}^{ort2}, D_{CMB}^{ort3}, D_{CMB}^{ort4}$	$D_{CTE}^{ort1}, D_{CTE}^{ort2}, D_{CTE}^{ort3}, D_{CTE}^{ort4}$	$D_{PTR}^{ort1}, D_{PTR}^{ort2}, D_{PTR}^{ort3}, D_{PTR}^{ort4}$
$D_{CMF}^{ort1} = \mathrm{H} \bullet \mathrm{E}_{CMV}$ $D_{CMF}^{ort2} = \mathrm{H} \bullet \mathrm{E}_{CMB}$ $D_{CMF}^{ort3} = \mathrm{H} \bullet \mathrm{E}_{CTE}$ $D_{CMF}^{ort4} = \mathrm{H} \bullet \mathrm{E}_{PTR}$	$D_{CMV}^{ort1} = \mathrm{H} \bullet \mathrm{E}_{CMF}$ $D_{CMV}^{ort2} = \mathrm{H} \bullet \mathrm{E}_{CMB}$ $D_{CMV}^{ort3} = \mathrm{H} \bullet \mathrm{E}_{CTE}$ $D_{CMV}^{ort4} = \mathrm{H} \bullet \mathrm{E}_{PTR}$	$D_{CMB}^{ort1} = \mathrm{H} \bullet \mathrm{E}_{CMF}$ $D_{CMB}^{ort2} = \mathrm{H} \bullet \mathrm{E}_{CMV}$ $D_{CMB}^{ort3} = \mathrm{H} \bullet \mathrm{E}_{CTE}$ $D_{CMB}^{ort4} = \mathrm{H} \bullet \mathrm{E}_{PTR}$	$D_{CTE}^{ort1} = \mathrm{H} \bullet \mathrm{E}_{CMF}$ $D_{CTE}^{ort2} = \mathrm{H} \bullet \mathrm{E}_{CMV}$ $D_{CTE}^{ort3} = \mathrm{H} \bullet \mathrm{E}_{CMB}$ $D_{CTE}^{ort4} = \mathrm{H} \bullet \mathrm{E}_{PTR}$	$D_{PTR}^{ort1} = \mathrm{H} \bullet \mathrm{E}_{CMF}$ $D_{PTR}^{ort2} = \mathrm{H} \bullet \mathrm{E}_{CMV}$ $D_{PTR}^{ort3} = \mathrm{H} \bullet \mathrm{E}_{CMB}$ $D_{PTR}^{ort4} = \mathrm{H} \bullet \mathrm{E}_{CTE}$
COLLINEARITY TEST - DISCRIMINANTS				
D_{CMF}^{col}	D_{CMV}^{col}	D_{CMB}^{col}	D_{CTE}^{col}	D_{PTR}^{col}
$D_{CMF}^{col} = \lVert \mathrm{H} \times \mathrm{E}_{CMF} \rVert$	$D_{CMV}^{col} = \lVert \mathrm{H} \times \mathrm{E}_{CMV} \rVert$	$D_{CMB}^{col} = \lVert \mathrm{H} \times \mathrm{E}_{CMB} \rVert$	$D_{CTE}^{col} = \lVert \mathrm{H} \times \mathrm{E}_{CTE} \rVert$	$D_{PTR}^{col} = \lVert \mathrm{H} \times \mathrm{E}_{PTR} \rVert$
DIRECTIONALITY TEST - DISCRIMINANTS				
D_{CMF}^{dir}	D_{CMV}^{dir}	D_{CMB}^{dir}	D_{CTE}^{dir}	D_{PTR}^{dir}
$\arccos\left(\frac{(\chi_{COMP} \bullet \varepsilon_{CMF})}{\lVert \chi_{COMP} \rVert \lVert \varepsilon_{CMF} \rVert}\right)$	$\arccos\left(\frac{(\chi_{COMP} \bullet \varepsilon_{CMV})}{\lVert \chi_{COMP} \rVert \lVert \varepsilon_{CMV} \rVert}\right)$	$\arccos\left(\frac{(\chi_{COMB} \bullet \varepsilon_{CMB})}{\lVert \chi_{COMB} \rVert \lVert \varepsilon_{CMB} \rVert}\right)$	$\arccos\left(\frac{(\chi_{CT} \bullet \varepsilon_{CTE})}{\lVert \chi_{CT} \rVert \lVert \varepsilon_{CTE} \rVert}\right)$	$\arccos\left(\frac{(\chi_{PT} \bullet \varepsilon_{PTR})}{\lVert \chi_{PT} \rVert \lVert \varepsilon_{PTR} \rVert}\right)$
MAGNITUDE TEST - DISCRIMINANTS				
$D_{CMF}^{pmt}, D_{CMF}^{smt}$	$D_{CMV}^{pmt}, D_{CMV}^{smt}$	$D_{CMB}^{pmt}, D_{CMB}^{smt}$	$D_{CTE}^{pmt}, D_{CTE}^{smt}$	$D_{PTR}^{pmt}, D_{PTR}^{smt}$
$D_{CMF}^{pmt} = \lVert \lVert \chi_{COMP} \rVert - \lVert \varepsilon_{CMF} \rVert \rVert$ $D_{CMF}^{smt} = \lVert \lVert H_{COMP} \rVert - \lVert H \rVert \rVert$	$D_{CMV}^{pmt} = \lVert \lVert \chi_{COMP} \rVert - \lVert \varepsilon_{CMV} \rVert \rVert$ $D_{CMV}^{smt} = \lVert \lVert H_{COMP} \rVert - \lVert H \rVert \rVert$	$D_{CMB}^{pmt} = \lVert \lVert \chi_{COMB} \rVert - \lVert \varepsilon_{MCB} \rVert \rVert$ $D_{CMB}^{smt} = \lVert \lVert H_{COMB} \rVert - \lVert H \rVert \rVert$	$D_{CTE}^{pmt} = \lVert \lVert \chi_{CT} \rVert - \lVert \varepsilon_{CTE} \rVert \rVert$ $D_{CTE}^{smt} = \lVert \lVert H_{CT} \rVert - \lVert H \rVert \rVert$	$D_{PTR}^{pmt} = \lVert \lVert \chi_{PT} \rVert - \lVert \varepsilon_{PTR} \rVert \rVert$ $D_{PTR}^{smt} = \lVert \lVert H_{PT} \rVert - \lVert H \rVert \rVert$
DISCRIMINANT VECTOR NORM				
$N_{CMF} = \lVert D_{CMF} \rVert$	$N_{CMV} = \lVert D_{CMV} \rVert$	$N_{CMB} = \lVert D_{CMB} \rVert$	$N_{CTE} = \lVert D_{CTE} \rVert$	$N_{PTR} = \lVert D_{PTR} \rVert$

Simulation results

Several scenarios of abrupt and progressive component degradation have been simulated to assess capability of developed diagnostic tool to capture induced component faults. Numerical simulations have been carried out running the engine model at full load steady-state conditions.

Component faults have been then subsequently injected as a step and\or ramp change of the component efficiency and\or capacity, and trends in health indices have been observed. Following component degradation \ fault modes have been considered in this study: compressor fouling, compressor VGV offset, combustor degradation, CT erosion and PT tip rub [Tab. 3.].

Tab. 5. Abrupt compressor fouling and progressive PT rub

FAULT	FAULT CLASSES									
	Compressor				Combustor		Compressor Turbine		Power Turbine	
	Compressor Fouling		VGV Offset		Combustor Degradation		CT Erosion		PT Tip Rub	
	$I_{\eta_{comp}}$	$I_{\Gamma_{comp}}$	$I_{\eta_{comp}}$	$I_{\Gamma_{comp}}$	$I_{\eta_{comb}}$	$I_{\Gamma_{comb}}$	$I_{\eta_{ct}}$	$I_{\Gamma_{ct}}$	$I_{\eta_{pt}}$	$I_{\Gamma_{pt}}$
	-2%	-3%	+1%	+9%	-4%	-	-2%	+3%	-4%	-
Abrupt	X	X								
Progressive									X	

Multiple faults simulation

Example of combined abrupt compressor fouling and progressive PT rub fault is presented in this section [Tab. 5.]. The fouled compressor is characterized by reduced compressor mass flow and deteriorated efficiency for any given speed. Thus, for a fouled compressor, the compressor capacity index $I_{\Gamma_{comp}}$ and the compressor efficiency index $I_{\eta_{comp}}$ would be observed as negative percentages. The effect of damage to the turbine blade tips normally affects the efficiency of the turbine rather than the flow and this is mainly due to flow capacity of the turbine being set by the choking of the nozzle guide vanes. Power turbine tip rub fault was simulated by negative ramp change in PT efficiency $I_{\eta_{pt}}$.

Figure Fig. 2. depicts health indices generated by performance tracking tool as a response on injected step change of compressor efficiency and capacity, and gradual decrease of power turbine efficiency, simulating combined abrupt compressor fouling and progressive PT tip rub.

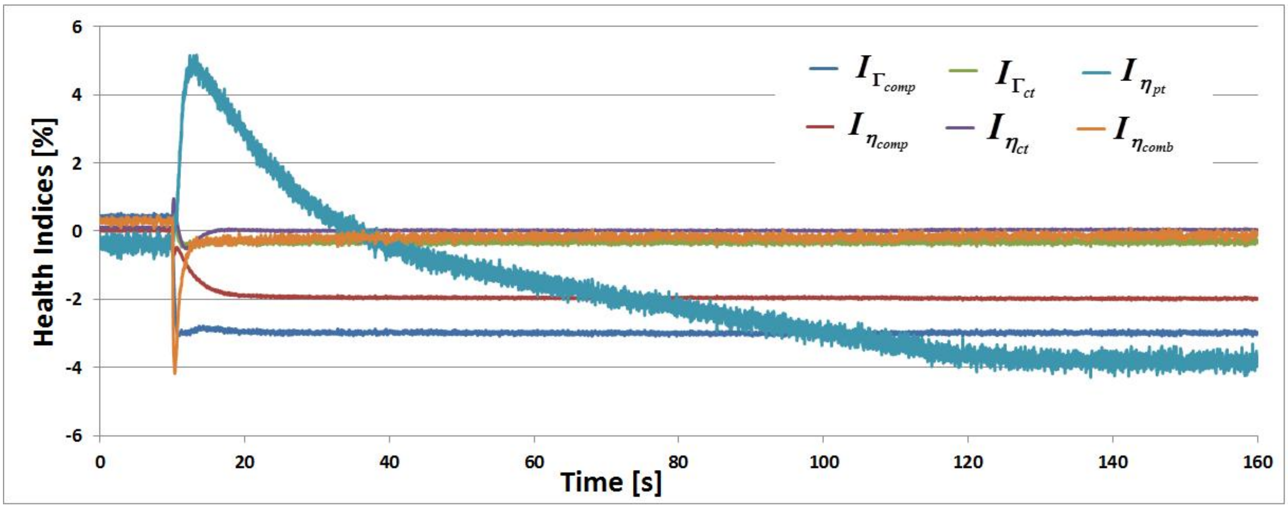


Fig. 2. Health indices - Abrupt compressor fouling and progressive PT tip rub

One can see that for implanted compressor and power turbine faults, health parameters were successfully identified by implemented observer, but identification was postponed due to measurement lag in the engine instrumentation. This effect is most pronounced in the trend of PT efficiency index which was predominantly affected with significant measurement lag of thermocouples in the engine hot gas path.

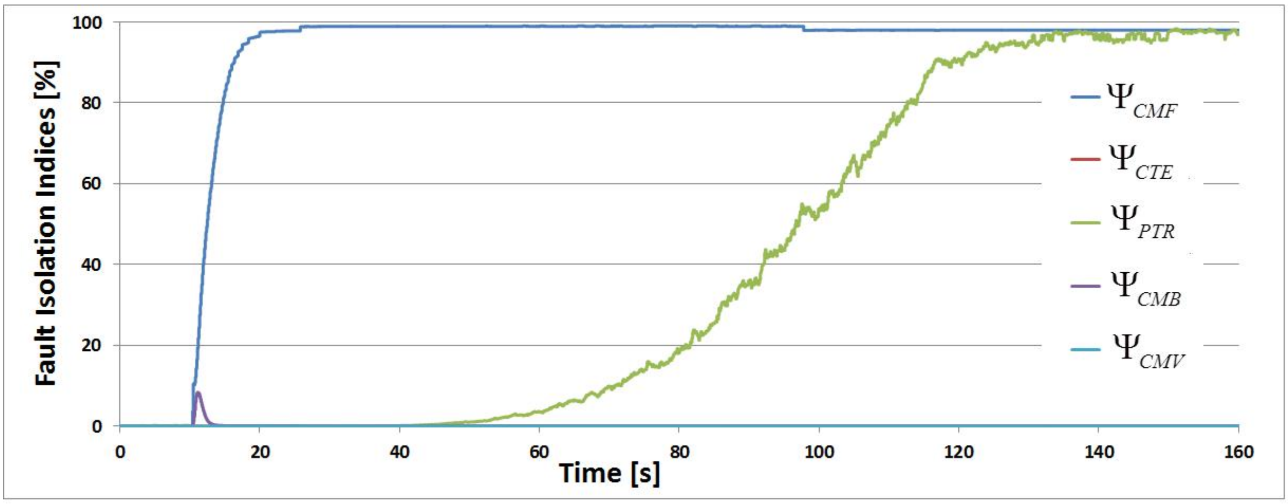


Fig. 3. Fault isolation indices - Abrupt compressor fouling and progressive PT tip rub

Response of deployed model-based diagnostic and isolation method on simulated multiple component faults is shown in figure Fig. 3. It can be seen that developed method successfully resolved simultaneously injected compressor and power turbine faults. In figure Fig. 3., one can see that abrupt compressor fouling is successfully classified by isolation index Ψ_{CMF} , whereas PT tip rub mode is captured by progressive increase in Ψ_{PTR} isolation index.

SUMMARY

Traditionally, most of the performance tracking and diagnostic methods of today are developed for gas turbine operating at steady state conditions. These methods usually use steady state thermodynamic performance models to generate predicted values for health parameters and information they provide is used mostly to initiate maintenance actions but not for autonomous on-line decision making in real-time.

In this contribution real-time on-line performance tracking tool, based on dynamic gas turbine model, is used for synthesis of engine health parameters, enabling in that way performance tracking and diagnostics under steady-state and transient conditions.

The devised diagnostic and isolation method provides a tool capable of detecting abrupt and gradual faults / degradation modes of the different gas-path components in the industrial gas turbine. The proposed method has been tested on the numerical test bed for a twin-shaft gas turbine engine by simulating single and multiple engine component faults and degradation modes.

Using proposed diagnostic and isolation framework, it is possible to customize developed method to cover various gas turbine types equipped with different engine instrumentation. The developed method enables autonomous on-line detection and isolation of gas turbine component faults and degradation modes.

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