FAULT DIAGNOSIS OF THERMAL TURBOMACHINES USING SUPPORT VECTOR MACHINES (SVM)

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Abstract

A method for detecting gas turbines malfunctions through aerothermodynamic and fast response measurements is presented. The proposed method is based on Support Vector Machines (SVM), a modern classification technique in the field of machine learning and artificial intelligence.

A brief description of SVM theory is given first, followed by a description of the overall diagnostic procedure, assisted by an Engine Performance Model (EPM). The method is evaluated through its effectiveness on three realistic fault diagnosis test cases: a) a turbofan engine, b) an axial and a radial compressor and c) sensors of a turbofan engine.

Application on these test cases demonstrates that the proposed SVM-based diagnostic method allows more accurate and reliable fault diagnosis, compared to other modern techniques in the field of gas turbines diagnostics.

Nomenclature

a_i	Lagrange multiplier, of point $\vec{x}_i$
A8IMP	Nozzle area
b	Constant term
CP	Classification Point
coef	Kernel variable
degree	Kernel variable
EPM	Engine Performance Model
f	vector of engine's health parameters
f_d	decision function
f_o	nominal value of vector f
gamma	Kernel variable
$K(\vec{x},\vec{z})$	Kernel function
l	number of points of the classes
Ld	Lagrange function
η_i	efficiency of component with entrance at station i
P_{amb}	ambient pressure
P_i	total pressure at station i of the engine
SE_i	efficiency factor at station i of the engine
SVM	Support Vector Machines
SW_i	flow factor at station i of the engine
T_i	total temperature at station i of the engine
u	filtered values of u´
u´	vector of measurements defining operating point
$\vec{w}$	oriented vector, vertical to separating hyperplane
W_i	gas mass flow rate at station i
WFE	fuel flow rate
XNHP	high pressure shaft rpm
XNLP	low pressure shaft rpm
$\vec{x}_i$	Point
$\vec{x}_{new}$	Point for classification
y	Label of the class (+1, -1)
Y	filtered values of Y´
Y_o	nominal value of quantity Y
Y´	vector of measured quantities on an engine
ΔY	percentage deviation of Y ('delta')

Subscripts

ref	Reference 'healthy' values

Introduction

During a gas turbine operation, problems may occur on engine components that may affect their performance and can lead even to severe malfunction of the engine.

To diagnose such operation faults in time, two kinds of diagnostic methods are used: a) estimation methods and b) classification methods. Estimation methods use a computational model of the engine and estimate the value of parameters, which are indicative of the operational state, with the aid of available measurements. In general these methods solve a minimization problem leaning on methods such as least squares, Kalman filters and their derivatives[10],[22],[25],[33],[34]-[35]. In classification methods fault signatures representing engine measurements are compared to the signatures of healthy operation of the engine or to the signatures of known engine faults. Aerothermodynamic measurements and fast response measurements could be the data that is used to produce the signatures. The most known representative of the classification methods is pattern recognition methods[3],[21], while Artificial Neural Networks (ANN) have also been used by many researchers[1],[1],[16],[29],[38].

In recent years a new classification technique, the Support Vector Machines (SVM), has become popular in the field of diagnostics. SVM were originally introduced in the statistical learning theory[37] and have been developed further[36],[2],[6],[27].

The method of SVM has been used in many sciences to solve classification problems, like in medicine, genetic, chemistry, economics, engineering, biology, etc[17],[20],[14],[13],[18].

Although the theory behind the SVM is not new and their applications in solving classification problems are many, their use for fault diagnosis in thermal turbomachines is recent. SVM have been used together with ANN to optimize the results of multiple faults detection of gas turbines[24]. SVM have also been used in a procedure to determine the state of readiness of gas turbines on combat ships in real time[5] and for fault diagnosis of a gas turbine that is used to move a Small UAV[19]. There are also, other works which used the SVM technique with cooperation with other techniques for fault diagnosis of thermal turbomachines[11],[26],[28]. All these works have demonstrated that SVM is a powerful tool for gas turbines diagnostics and further research on the field is required.

This paper introduces an SVM algorithm developed for fault diagnosis in thermal turbomachines, where it acts as a standalone diagnostic method. The potential of the SVM algorithm is demonstrated through applications on real and simulated fault cases.

Support Vector Machines. A brief description

A thorough description of the principals of the SVM and their equations is provided by Burges[4]. In this paper a brief description of SVM basics is attempted, to support the description of the proposed diagnostic method that follows.

In classification problems, SVM separate two classes (label: y=1 or y=-1) with a hyperplane which is the boundary between these classes, set to the maximum distance from both classes simultaneously.

The hyperplane is defined by the outmost points of the classes which are called Support Vectors.

The position of a point, representing a vector, with regard to the separating line determines in which class the vector is classified into.

The simplest case of SVM is the linear SVM with fully separable classes. A graphical representation of an example of two classes separated SVM, in this case is shown in Fig.1.

The equation of the separating line (hyperplane, in general) is given:

$$\vec{w} \cdot \vec{x}_i + b = 0 \qquad (1)$$

In this relation $\vec{w}$ is an oriented vector, vertical to separating hyperplane, $\vec{x}_i$ represents the coordinates of the points of the separating line and b is the constant of the separating line's equation.

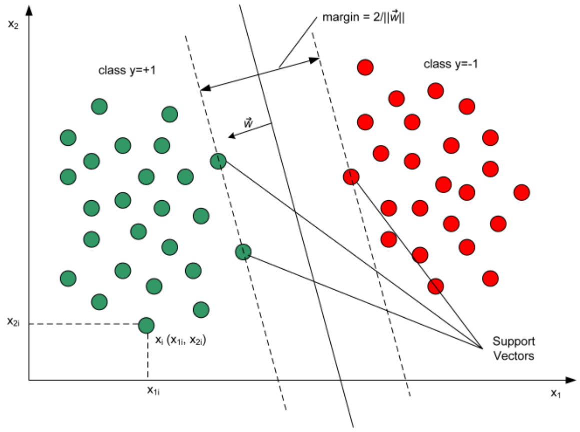

Fig. 1: Visualization of the SVM method

The optimal separating hyperplane is obtained by maximizing the margin: $2/||\vec{w}||$ with the restriction of:

$$y_i(\vec{w}\cdot\vec{x}_i + b) - 1 \geq 0, \quad \forall i \qquad (2)$$

Where, y_i, is either +1 or -1, depending on which class point $\vec{x}_i$ belongs to.

The above margin maximization problem with the Lagrange transformation becomes:

$$\left[\begin{array}{l} \boldsymbol{max} : Ld = \sum_{i=1}^{l} a_i - \frac{1}{2}\sum_{i,j=1}^{l} a_i a_j y_i y_j \vec{x}_i \vec{x}_j \\ \sum_{i=1}^{l} a_i y_i = 0 \\ a_i \geq 0 \end{array}\right] \qquad (3)$$

where a_i is the Lagrange multiplier of point $\vec{x}_i$, out of a total number of l points.

In other words, the problem is to determine the Lagrange multipliers (a_i) of the points. Support Vectors are those points that have positive Lagrange multipliers ($a_i>0$).

As described by Burges[4], $\vec{w}$ can be found through equation:

$$\vec{w} = \sum_{i=1}^{l} a_i y_i \vec{x}_i \qquad (4)$$

while, The constant b can finally be estimated by equation:

$$\vec{w}\cdot\vec{x}_i + b = \pm 1 \Rightarrow \sum_{i=1}^{l} a_i y_i \vec{x}_i \vec{x}_j + b = \pm 1 \qquad (5)$$

Once $\vec{w}$ and b are defined, the separating hyperplane is known. To determine into which class a new point ($\vec{x}_{new}$) must be classified, the relative position of that point from the separating hyperplane is determined through the decision function:

$$sign(f_d) = sign(\vec{w}\cdot\vec{x}_{new} + b) \qquad (6)$$

If the sign of the decision function is positive the point is classified into the class with label y=1 and if the sign is negative the point is classified into the class with label y=-1.

In the general case, SVM may involve non-separable classes and/or non-linear hyperplane. In that case Eq.3 is considered in its general form:

$$\left[\begin{array}{l} \boldsymbol{max} : Ld = \sum_{i=1}^{l} a_i - \frac{1}{2}\sum_{i,j=1}^{l} a_i a_j y_i y_j K(\vec{x}_i \vec{x}_j) \\ \sum_{i=1}^{l} a_i y_i = 0 \\ a_i \geq 0 \end{array}\right] \qquad (7)$$

In this relation, $K(\vec{x}_i, \vec{x}_j)$ is the result of a Kernel function[4].

In this study four kernels have been considered: the Linear kernel, the Polynomial kernel, the RBF kernel and the Sigmoid kernel. The formula of each kernel is, respectively:

$$K(\vec{x}, \vec{z}) = \vec{x}\cdot\vec{z} \qquad (8)$$

$$K(\vec{x}, \vec{z}) = (gamma\cdot(\vec{x}\cdot\vec{z}) + coef)^{\boldsymbol{degree}} \qquad (9)$$

$$K(\vec{x}, \vec{z}) = e^{-gamma\cdot\|\vec{x}-\vec{z}\|^2} \qquad (10)$$

$$K(\vec{x}, \vec{z}) = tanh(gamma\cdot(\vec{x}\cdot\vec{z}) - coef) \qquad (11)$$

independent variables *Gamma, coef, degree* are usually determined experimentally.

Moreover, in the general case, the decision function of Eq.6 becomes:

$$sign(f_d) = sign(\sum_{i=1}^{l} y_i a_i K(\vec{x}_{new}, \vec{x}_i) + b) \qquad (12)$$

The above description involves only two classes. Every SVM can separate two classes only, so for the separation of more classes, more SVM are needed (multi-classification problem). For the multiclassification problem, among other methods four are most commonly used[8]. These are: one-against-all, all-together, one-against-one and DAGSVM.

In the present work the one-against-one method with “max wins” classification technique, has been considered. According to the one-against-one method, all possible pairs of classes are considered and every pair is separated with a hyperplane. Thus, the number of the decision functions is equal to the number of possible pairs.
For the classification, the “max wins” technique is used. According to this technique, all decision functions are applied for the classification of a single point. Each time this point is classified into a class, this class is given one classification point (CP). Finally, the point is classified into the class with the maximum number of CPs.

Overview of the diagnostic procedure

A schematic presentation of the overall procedure of the proposed diagnostic method is shown in Fig.2.

A filtering procedure on the measurements acquired from the engine acts as auxiliary but essential element of the diagnostic procedure. A set of measurement readings that consists of vectors u´ of set point parameters and vector Y´ of condition monitoring parameters is preprocessed through filtering procedure that minimizes the effect of the noise, providing a set of measurements (u, Y) closer to the actual ones. Filtering methods for this purpose have been proposed by other researchers[12].

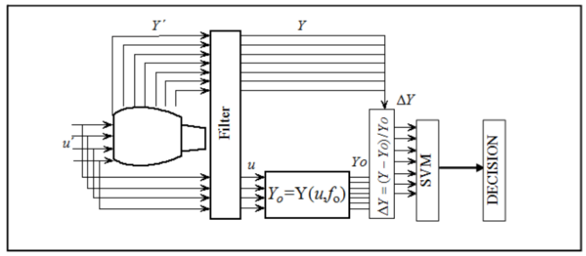

Fig. 2: Flowchart of the overall procedure of the proposed diagnostic method.

From these filtered measurements, the percentage deviations ΔY of measurements Y from their nominal values Y_o are calculated.

Measurement nominal values (Y_o) are estimated with the assist of an Engine Performance Model (EPM) that involves acquired measurements (u, Y) with engine health parameters (f), through a functional relation:

$$Y = Y(u, f) \qquad (13)$$

applied for the fault free operation of the engine.

The use of deltas as input provides data that have a weak dependence on operating conditions[23].

The deltas of the measurements form the input pattern to the SVM. The role of the SVM is to classify this input pattern, into the correct class. For the problem at hand each class on the SVM represents a specific fault of the engine, expressed through the deviation of specific health parameters, within specific range. Therefore, the classes of the SVM represent a predefined set of possible faults of the engine.

Finally, our decision on which fault occurs, if any, relies on the classification made by SVM.

Applications of the proposed diagnostic procedure

Application on a turbofan benchmark case

In order to give a more clear picture of the way the proposed method is set-up and to evaluate its effectiveness, application to a turbofan test case is presented. Apart from its illustrative nature, the test case represents also a situation of practical interest in today's jet engines applications.

The type of engine for this application is described in APPENDIX A. It is selected as it has been used in applications of various diagnostic methods by the authors and other researchers and can be considered to constitute a benchmark case[9],[15],[23],[31].

Generation of classes

In order to assess the diagnostic ability of the proposed method, health condition cases covering situations expected to be encountered in practice are tested. In total, 133 engine health conditions have been considered. The first 132 conditions represent various faulty operations of the engine represented by deviations of one or more health parameters, each time, within the range of ±[0.5%, 2.5%]. Extent engine faults leading to health parameters deviations larger than ±2.5% are not examined here, since the present work focuses on small or moderate faults that are, generally hard to detect. The last health condition considered represents the healthy operation of the engine, represented by not significant deviation of the health parameters.

In the present application any deviation within the range of (-0.5%, +0.5%) is considered not significant.

The patterns of these cases resulted by the EPM.

Method evaluation

A set of fault scenarios has been examined, covering various possible faults in all individual components on the engine. This set of cases has been defined by Curnock[7] and the fault cases have been used for evaluation by several researchers and diagnostic methods[9],[15],[23]. The considered fault scenarios and the deviations of their health parameters are shown in Table 1.

Fault Scenario	Deviation of health parameters	Fault Scenario	Deviation of health parameters
a	ΔSW2=-0.7%, ΔSE2=-0.4%	h	ΔSE41=-1%
	ΔSW12=-1%, ΔSE12=-0.5%	i	ΔSE49=-1%
b	ΔSE12=-1%	j	ΔSW49=+1%, ΔSE49=-0.4%
c	ΔSW26=-1%, ΔSE26=-0.7%	k	ΔSW49=-1%
d	ΔSE26=-1%	l	ΔSW49=+1%, ΔSE49=-0.6%
e	ΔSW26=-1%	m	A8IMP=+1%
f	ΔSW41=+1%	n	A8IMP=-1%
g	ΔSW41=-1%, ΔSE41=-1%	o	A8IMP=+2%

Table 1: Fault scenarios and their health parameters' deviation

For each examined fault case data, namely vectors u and Y, from a sequence of fifty points are used. These are realistic typical readings taken every five minutes over the cruise sections of a flight.

Table 2 summarizes the results of the SVM method, incorporating the RBF kernel.

Fault case	SVM		
	Actual deviations of health parameters	Health parameters and deviations as found by SVM	Point of localisation
a	SW2=-0.7%, SE2=-0.4% SW12=-1%, SE12=-0.5%	SW2=-0.7%, SE2=-0.4% SW12=-0.7%, SE12=-0.4%	6
b	SE12=-1%	SE12=-1.2%	11
c	SW26=-1%, SE26=-0.7%	SE2=-2.25%	47
d	SE26=-1%	SE26=-1.2%	11
e	SW26=-1%	SW26=-1.2%	33
f	SW41=+1%	SW41=+0.75%	9
g	SW41=-1%, SE41=-1%	SW41=-1.2%, SE41=-1.2%	2
h	SE41=-1%	SE41=-1.2%	8
i	SE49=-1%	SE49=-1.2%	1
j	SW49=-1%, SE49=-0.4%	SW49=-1.2%, SE49=-0.6%	41
k	SW49=-1%	SW49=-1.2%	1
l	SW49=+1%, SE49=-0.6%	SW49=+0.75%, SE49=-0.4%	33
m	A8IMP=+1%	A8IMP=+1.3%	46
n	A8IMP=-1%	A8IMP=-1.2%	5
o	A8IMP=+2%	A8IMP=+1.8%	11

Table 2: Diagnostic performance on a set of 15 benchmark fault cases

In this table, the actual and the estimated by the SVM method deviations of each health parameter for each fault case is presented, along with the point of localization. This is the point, out of the 50, for each fault case, where the diagnostic conclusion is stabilized. This means that all points after the localization point are classified in the same class. The estimated deviations of each health parameter represent the middle value of this parameter on the class where the examined fault case has been classified into.

From this table, it is concluded that in 14 out of 15 cases all actually deviated health parameters are identified correctly, providing also an accurate estimation of the magnitude of health parameters deviation. These results consist an improvement on both the number of fault cases detected correctly and the accuracy of the diagnosis, in comparison to other methods that have been applied on the same fault cases[30],[32].

Application on gas turbine compressors

The proposed fault diagnosis method has also been applied in the cases of an axial and a radial compressor. In both cases, available data consists of aerothermodynamic and fast response measurements.

In the radial compressor case 3 faults are examined (Diffuser distortion, Impeller fouling and Inlet distortion). Available data consists of 4 sets of 7 thermodynamic measurements and 1 fast response measurement (accelerometer). The diagnostic procedure has been applied separately for the aerothermodynamic and the fast response measurements using four different Kernels.

For the axial compressor 4 faults have been examined.

Available data also consists of 4 sets of 7 thermodynamic measurements and 4 fast response measurements (3 accelerometers and 1 pressure transducer). The diagnostic procedure has been applied separately for the aerothermodynamic and the fast response measurements.

In both compressor cases, three sets of measurements were used to populate the SVM classes, while the fourth set is used for evaluation of the method.

Since the available data are quite few, a number of additional patterns are generated. For each compressor, the average of all possible combination of the existing four patterns is considered. This leads to a set of 11 patterns for each fault.

Fig.3 demonstrates the score of the examined faults. As we see, although the score of the actual data is very poor, due to the limited number of available measurements, the use of additional patterns improved importantly the method efficiency.

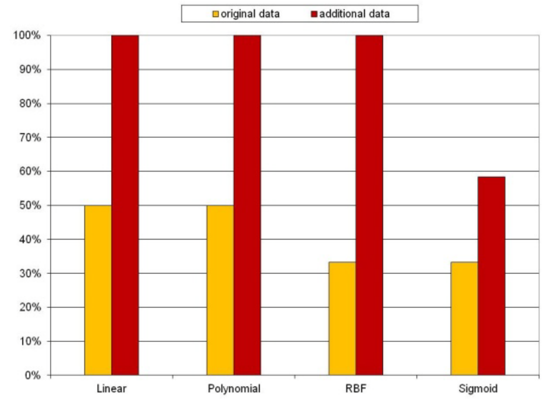

Fig. 3: Success rate for each Kernel for the radial compressor.

Application on sensor faults

Since any fault diagnosis attempt relies on available data, reliable measured data play a key role to the overall diagnostic procedure. The presence of a sensor fault may affect importantly the engine diagnosis. Thus, data validation must precede any other diagnostic attempt and, consequently, any method allowing data validation must be efficient regardless the actual health condition of the engine itself.

The proposed diagnostic procedure has been applied for the detection of engine sensor faults, with simultaneous deviation of health parameters.

The procedure has been applied in the case of the turbofan engine examined before and described in APPENDIX-A.

<u>Generation of classes</u>

For the sensor fault diagnosis, sensor deviations of up to ±2% have been considered, while deviations within the range of ±0.1% are not considered as sensor faults. Sensor biases are considered at the simultaneous presence of engine component faults represented by deviations of the engine health parameters within the range of ±2.5%.

In total, 11 classes have been considered, where the first ten represent each a faulty sensor, while the last class represents the case where no sensor fault occurs. These classes are presented in Table 3.

Class	1	2	3	4	5	6	7	8	9	10	11
Faulty Sensor	T1	P1	WFE	XNLP	XNHP	P13	P3	T3	T6	T13	No Fault

Table 3: Considered classes for sensor fault diagnosis

In total, 943 patterns have been generated through the EPM that populate the 11 aforementioned classes.

Method evaluation

In total, 460 sensor fault cases have been considered. These cases represent sensor biases of ±1.5%, for all 10 considered sensors (see Table 3), with the simultaneous presence of component faults represented by deviation of health parameters. The patterns of these cases resulted by the EPM.

In this application all 4 different kernels were used. Table 4 summarizes the number of wrong classifications and the success rate for each kernel.

SVM Kernel	number of wrong classifications	success rate
Linear	460	0.0%
Polynomial	43	93.3%
Sigmoid	450	1.6%
RBF	1	99.8%

Table 4: Diagnostic performance for sensors case

From this table it can be concluded, that when it comes to RBF Kernel function, SVM method becomes very accurate in the detection of faulty sensors at the simultaneous presence of engine component faults.

Concluding remarks

The use of Support Vector Machines for detection and isolation of gas turbine faults has been presented. The proposed diagnostic technique involves the use of an EPM, to produce data to form the signatures of the faults.

The way such a procedure can be set up is presented and applications to a specific type of a turbofan engine, for the detection of component and sensor faults, and two compressors, a radial and an axial, are demonstrated.

The effectiveness of the proposed method has been demonstrated by its strong diagnostic ability with various fault scenarios.

The main conclusion concerning the performance of the presented method is its ability to handle efficiently the problem of fewer measurements than parameters in gas path analysis.

This conclusion becomes more important since it indicates that reliable diagnostic SVM can be built from mathematical models, without the need of hard to find data of faulty operations on which other methods are based.

APPENDIX-A: ENGINE LAYOUT AND REPRESENTATION

The considered gas turbine is a modern civil aviation turbofan engine.

The operating point of the engine is defined by measurement of ambient pressure (Pamb), inlet pressure and temperature (P1,T1) and fuel consumption (WFE), forming vector u, while rotating speeds of the two spools (XNLP, XNHP) and pressures and temperatures at several stations (P13, T13, P3, T3, T6) form vector Y.

The health condition of the engine components is represented by flow and efficiency factors of each engine component at stations 12, 2, 26, 41, 49, 8, forming vector f, along with parameter A8IMP representing the nozzle area. For a component with entrance at station i of the engine we have:

Flow factor:

$$SW_i = (W_i \cdot \sqrt{T_i} / p_i)/(W_i \cdot \sqrt{T_i} / p_i)_{ref} \quad (14)$$

Efficiency factor:

$$SE_i = \eta_i / (\eta_i)_{ref} \quad (15)$$

The quantitative interrelation among the health parameters and the measurements is expressed through an Engine Performance Model (EPM)[33] and adapted to individual engines to reproduce accurately their performance.

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