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

C. Kalathakis
Research Assistant

C. Romesis
Research Associate

N. Aretakis
Lecturer

K. Mathioudakis
Professor

Laboratory of Thermal Turbomachines
National Technical University of Athens

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- Description of the diagnostic problem
- Support Vector machines (SVM)
  - o The mechanism behind
  - o The general classification case
- Application on a Turbofan Engine
  - o Aerothermodynamic benchmark fault cases
  - o Sensor fault diagnosis
- Application on compressor faults
  - o The radial compressor case
  - o The axial compressor case
- Summary - Conclusions

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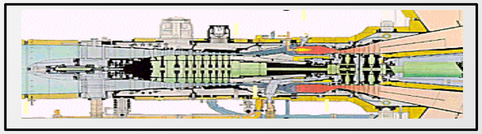
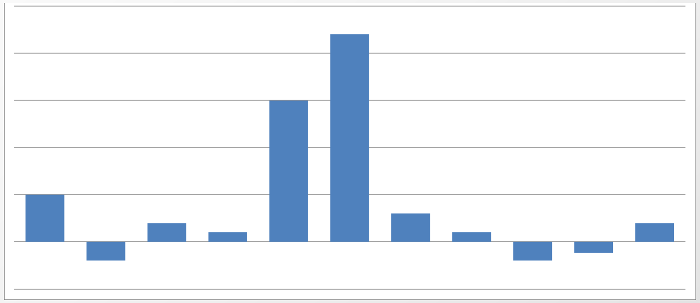
Description of the diagnostic problem

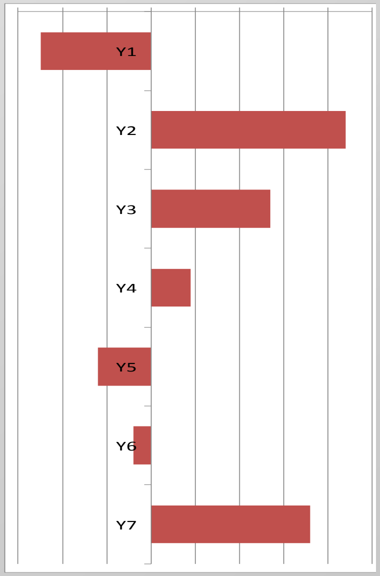
u (operating point)
f (health condition)

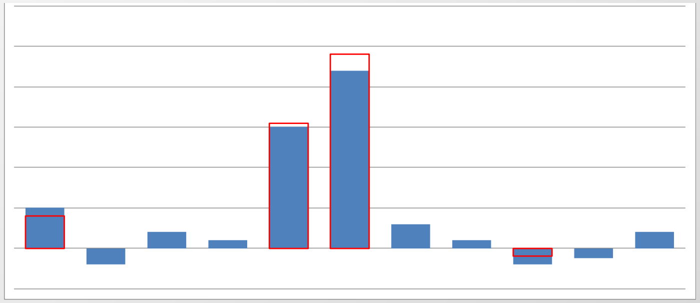


Y (measurements)



Engine faults(represented by a health parameters deviation), cause a corresponding measurement deviation.





Given a set of measurements the goal is to estimate the health parameters deviation due to fault.

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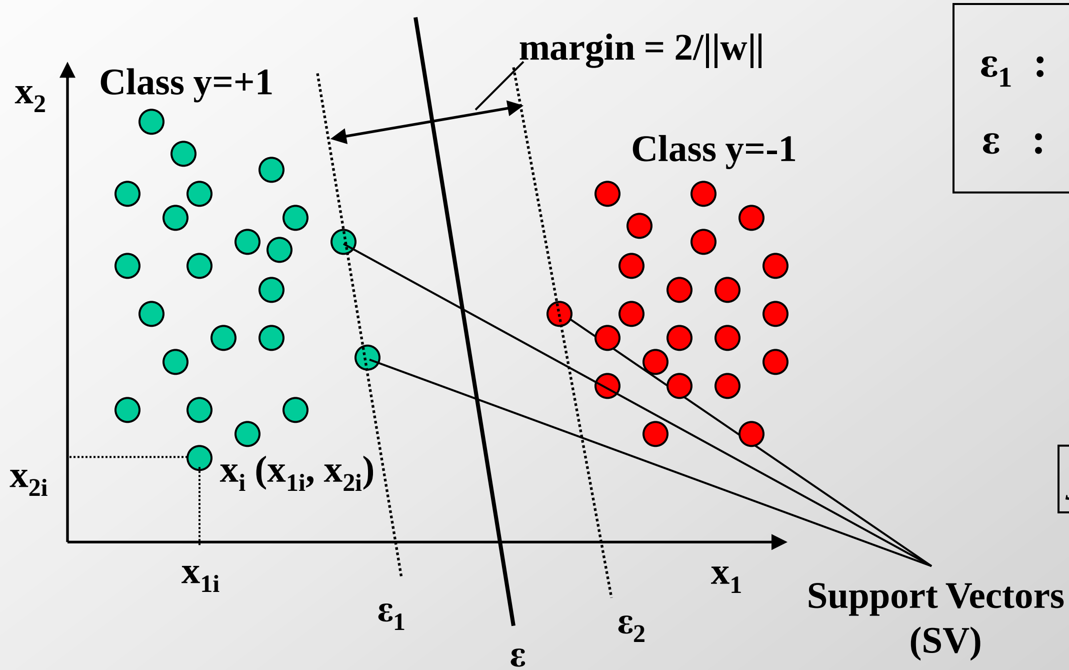
Support Vector Machines (SVM)

SVM is a supervised learning technique used for pattern classification



$$\varepsilon_1 : \ \vec{w}\cdot\vec{x}+b=+1 \quad \varepsilon_2 : \vec{w}\cdot\vec{x}+b=-1$$
$$\varepsilon : \ \vec{w}^{*}\cdot\vec{x}+b^{*}=0$$

<u>All points satisfy:</u>

$$\vec{w}\cdot\vec{x}+b\geq+1, \quad y=+1$$
$$\vec{w}\cdot\vec{x}+b\leq-1, \quad y=-1$$
$$\boxed{y_i(\vec{w}\cdot\vec{x}_i+b)-1\geq 0, \quad \forall i}$$

Linear SVM, with fully separable classes of 2D points

Support Vector Machines (SVM)

Quadratic Programming optimization problem

Laplace transform

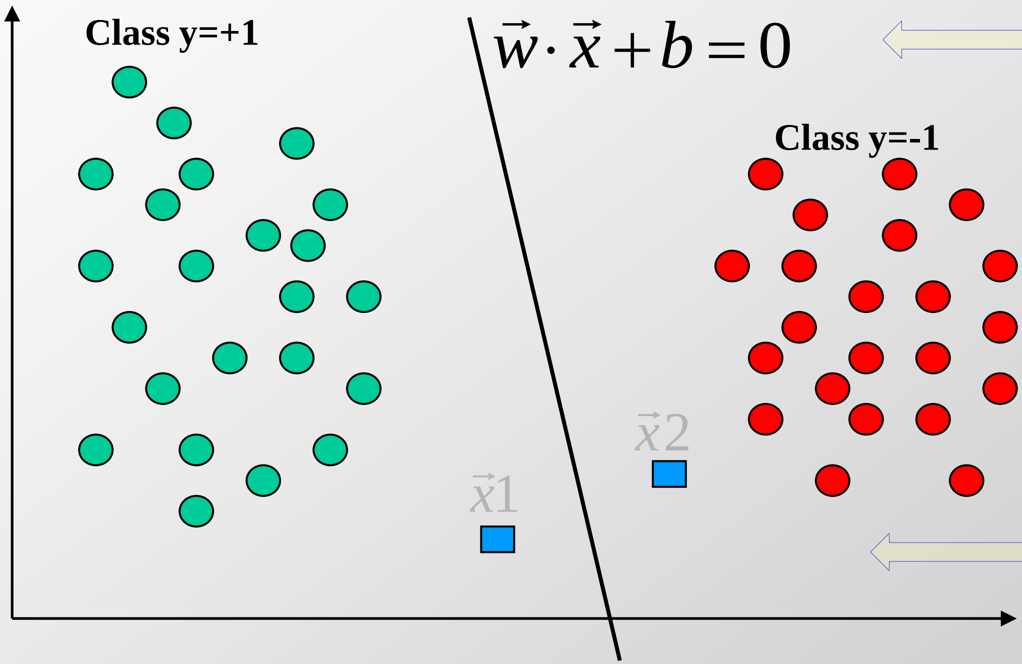
Karush-Kuhn-Tucker (KKT) conditions

$$\left[\begin{array}{l} \boldsymbol{max}\left(\dfrac{2}{\|\vec{w}\|}\right) \rightarrow \boldsymbol{min}\left(\dfrac{1}{2}\|\vec{w}\|^2\right) \\ \\ y_i\boldsymbol{(}\vec{w}\cdot\vec{x}_i + b\boldsymbol{)} - 1 \geq 0\boldsymbol{,} \quad \forall i \end{array}\right]$$

$$\left[\begin{array}{l} \max : Ld = \sum_{i=1}^{l} a_i - \dfrac{1}{2}\sum_{i,j=1}^{l} a_i a_j y_i y_j x_i x_j \\ \\ \sum_{i=1}^{l} a_i y_i = 0 \\ \\ a_i \geq 0 \end{array}\right]$$

Support Vector Machines (SVM)

Pattern classification



$$\vec{w}^* = \sum_{i=1}^{l} a_i y_i \vec{x}_j \;\longrightarrow\; \vec{w}^*$$

$$\vec{w}^* \cdot \vec{x}_i + b^* = \pm 1 \longrightarrow b^*$$

$$\vec{w}^* \cdot \vec{x}1 + b^* > 0 \Rightarrow \vec{x} \in y = +1$$

$$\vec{w}^* \cdot \vec{x}2 + b^* < 0 \Rightarrow \vec{x} \in y = -1$$

Support Vector Machines (SVM) – The general case

Non-linear SVM, with non-separable classes

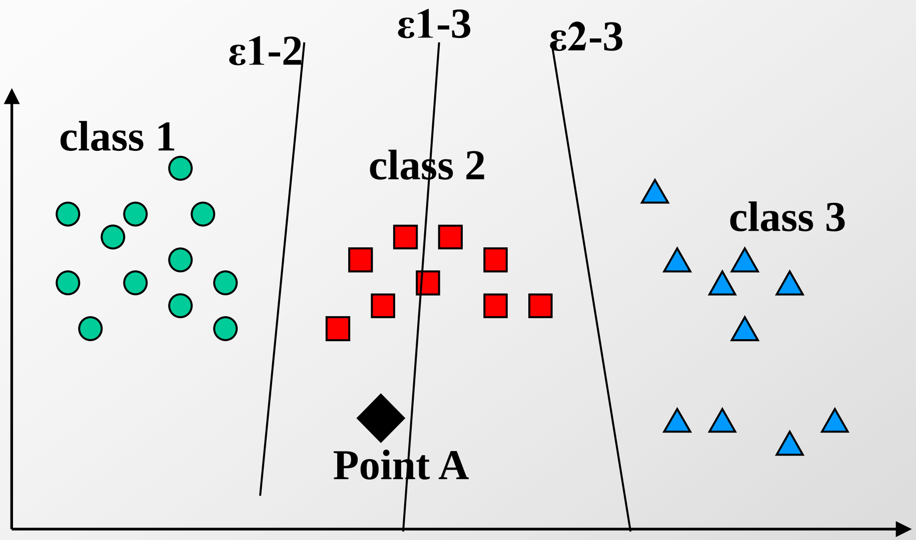
$$\left[\begin{array}{l} \boldsymbol{max:}\ Ld = \sum_{i=1}^{l} a_i - \frac{1}{2}\sum_{i,j=1}^{l} a_i a_j y_i y_j \cdot K\left(x_i, x_j\right) \\ \sum_{i=1}^{l} a_i y_i = 0 \\ \\ 0 \le a_i \le C \end{array}\right]$$

Considered Kernel functions:

$K(x,y) = x \cdot y$	**Linear kernel**
$K(x,y) = (gama \cdot (x \cdot y) + coef\,)^{\mathrm{deg}ree}$	**Polynomial kernel**
$K(x,y) = e^{-gama \cdot \lVert x-y \rVert^2}$	**RBF kernel**
$K(x,y) = \tanh(gama \cdot (x \cdot y) - coef\,)$	**Sigmoid kernel**

Support Vector Machines (SVM)

Multiclassification; the case of more classes involved

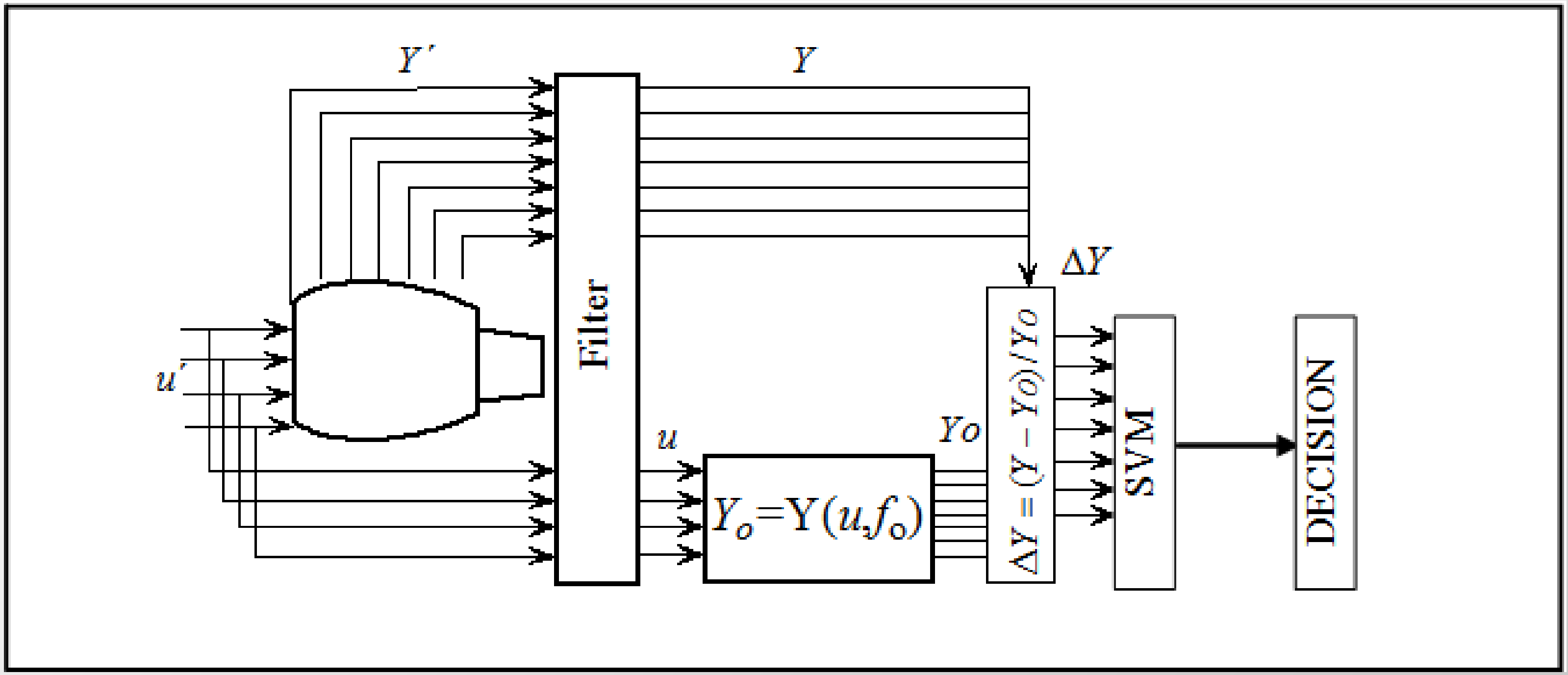


- One-against-all
- All-together
- One-against-one
- DAGSVM

Max-wins classification

	Class-1	Class-2	Class-3
ε1-2	0	1	0
ε1-3	1	0	0
ε2-3	0	1	0
total	1	2	0

Overall diagnostic procedure



Filtered percentage deviations of available measurements form the input patterns

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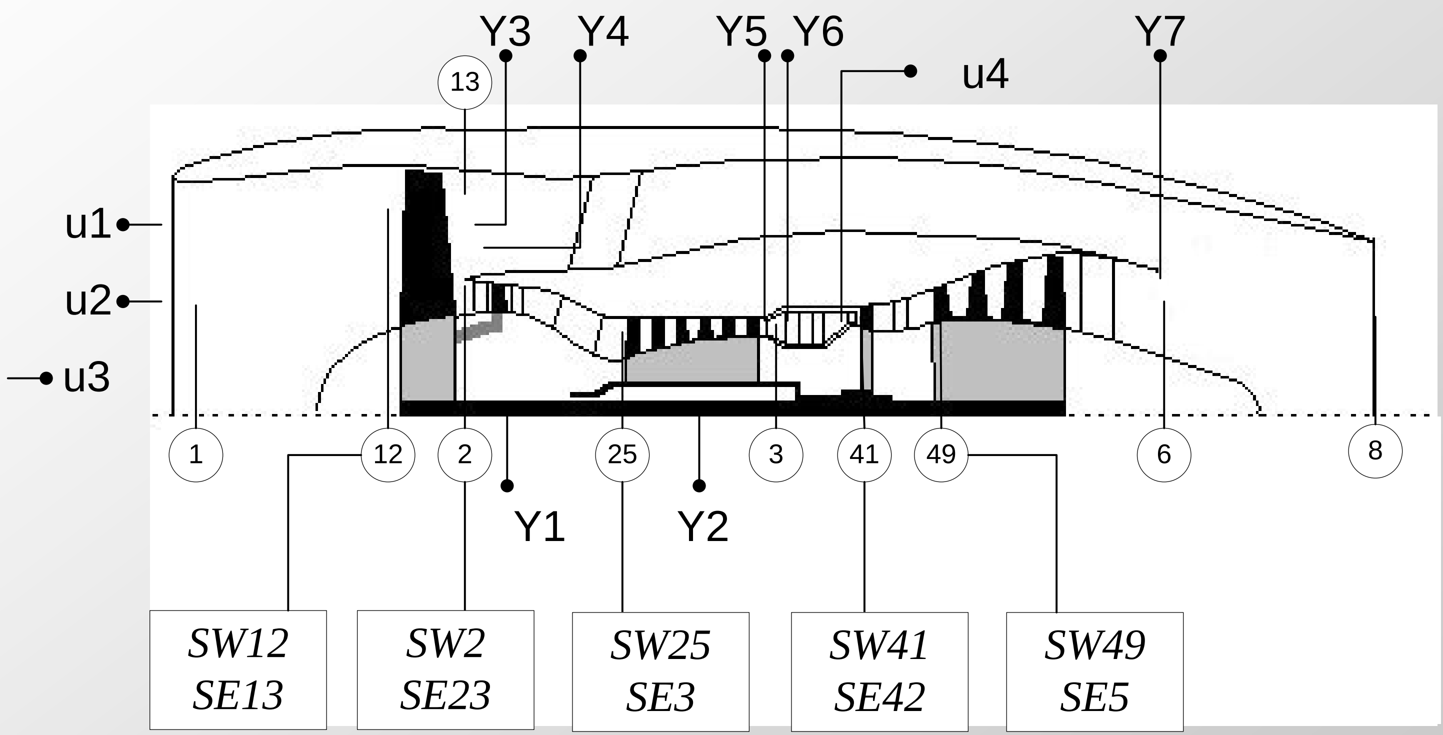
Application on a Turbofan engine



Twin spool, high-by-Pass ratio, turbofan engine used as a test case

Application on a Turbofan engine

no. of classes	parameter deviations	no. of classes	parameter deviations
11	Δfi=α, α ∈[-2.5%, -2.0%], f_i=A8IMP, SWi, SEi, i=12,2,26,41,49	3	(ΔSWi=α, ΔSEi=-α), α∈(1.0%, 1.5%], i=26,41,49
11	Δfi=α, α ∈(-2.0%, -1.5%], f_i=A8IMP, SWi, SEi, i=12,2,26,41,49	3	(ΔSWi=α, ΔSEi=-α), α∈(1.5%, 2.0%], i=26,41,49
11	Δfi=α, α ∈(-1.5%, -1.0%], f_i=A8IMP, SWi, SEi, i=12,2,26,41,49	3	(ΔSWi=α, ΔSEi=-α), α∈(2.0%, 2.5%], i=26,41,49
11	Δfi=α, α ∈(-1.0%, -0.5%], f_i=A8IMP, SWi, SEi, i=12,2,26,41,49	3	(ΔSWi=α, ΔSEi=-α/2), α∈[0.5%, 1.0%], i=26,41,49
4	Δfi=α, α ∈[0.5%, 1.0%], f_i=A8IMP, SWi, i=26,41,49	3	(ΔSWi=α, ΔSEi=-α/2), α∈(1.0%, 1.5%], i=26,41,49
4	Δfi=α, α ∈(1.0%, 1.5%], f_i=A8IMP, SWi, i=26,41,49	3	(ΔSWi=α, ΔSEi=-α/2), α∈(1.5%, 2.0%], i=26,41,49
4	Δfi=α, α∈(1.5%, 2.0%], f_i=A8IMP, SWi, i=26,41,49	3	(ΔSWi=α, ΔSEi=-α/2), α∈(2.0%, 2.5%], i=26,41,49
4	Δfi=α, α∈(2.0%, 2.5%], f_i=A8IMP, SWi, i=26,41,49	1	(ΔSW12=α, ΔSE12=α, ΔSW2=α, ΔSE2=α), α∈[-2.5%, -2.0%]
5	(ΔSWi=α, ΔSEi=α), α∈[-2.5%, -2.0%], i=12,2,26,41,49	1	(ΔSW12=α, ΔSE12=α, ΔSW2=α, ΔSE2=α), α∈(-2.0%, -1.5%]
5	(ΔSWi=α, ΔSEi=α), α∈(-2.0%, -1.5%], i=12,2,26,41,49	1	(ΔSW12=α, ΔSE12=α, ΔSW2=α, ΔSE2=α), α∈(-1.5%, -1.0%]
5	(ΔSWi=α, ΔSEi=α), α∈(-1.5%, -1.0%], i=12,2,26,41,49	1	(ΔSW12=α, ΔSE12=α, ΔSW2=α, ΔSE2=α), α∈(-1.0%, -0.5%]
5	(ΔSWi=α, ΔSEi=α), α∈(-1.0%, -0.5%], i=12,2,26,41,49	1	(ΔSW12=α, ΔSE12=α/2, ΔSW2=α, ΔSE2=α/2), α∈[-2.5%, -2.0%]
5	(ΔSWi=α, ΔSEi=α/2), α∈[-2.5%, -2.0%], i=12,2,26,41,49	1	(ΔSW12=α, ΔSE12=α/2, ΔSW2=α, ΔSE2=α/2), α∈(-2.0%, -1.5%]
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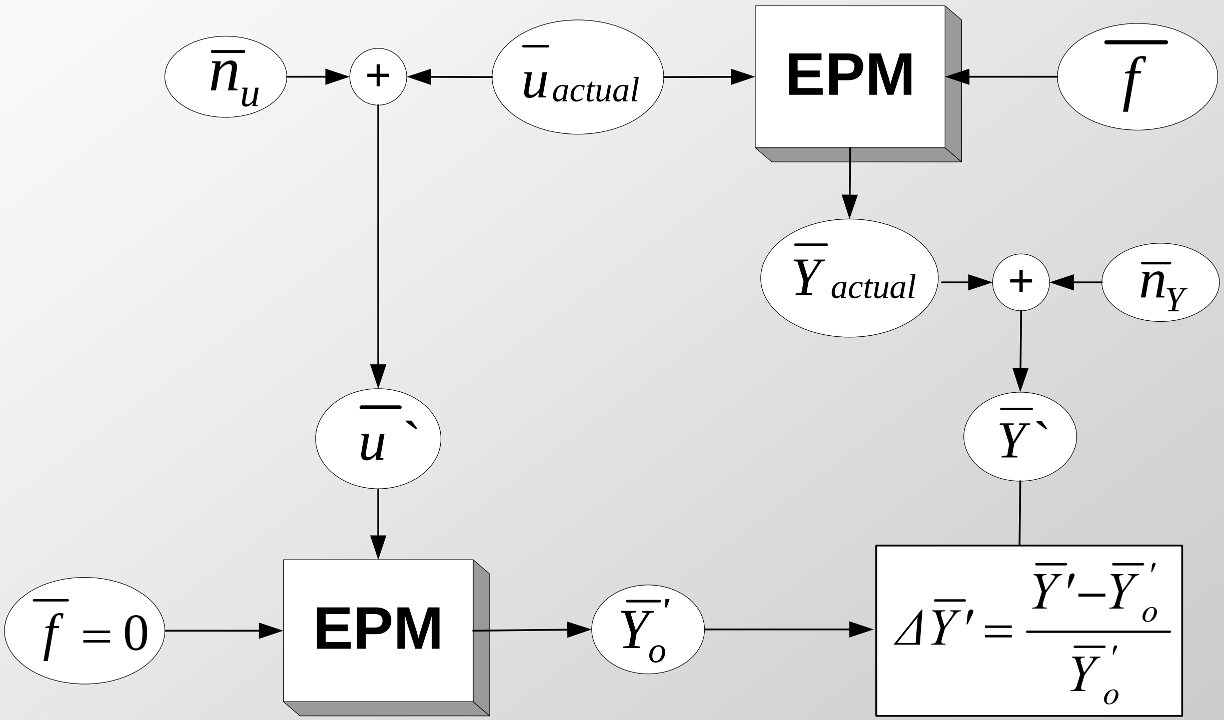
5	(ΔSWi=α, ΔSEi=α/2), α∈(-1.5%, -1.0%], i=12,2,26,41,49	1	(ΔSW12=α, ΔSE12=α/2, ΔSW2=α, ΔSE2=α/2), α∈(-1.0%, -0.5%]
5	(ΔSWi=α, ΔSEi=α/2), α∈(-1.0%, -0.5%], i=12,2,26,41,49	1	any within range (-0.5%, +0.5%)
3	(ΔSWi=α, ΔSEi=-α), α∈[0.5%, 1.0%], i=26,41,49	**133**	**total no. of classes**

A number of classes were considered, each indicating a specific fault condition, represented by a deviation of health parameters within a range of values

Application on a Turbofan engine



Classes populated with simulated patterns representing health parameters deviation within the range of ±[0.5%, 2.5%]

Application on a Turbofan engine

fault case	actual parameter deviation	estimated parameter deviation
a	SW2=-0.7%, SE2=-0.4% SW12=-1%, SE12=-0.5%	SW2=-0.7%, SE2=-0.4% SW12=-0.7%, SE12=-0.4%
b	SE12=-1%	SE12=-1.2%
c	SW26=-1%, SE26=-0.7%	SE2=-2.25%
d	SE26=-1%	SE26=-1.2%
e	SW26=-1%	SW26=-1.2%
f	SW41=+1%	SW41=+0.75%
g	SW41=-1%, SE41=-1%	SW41=-1.2%, SE41=-1.2%
h	SE41=-1%	SE41=-1.2%
i	SE49=-1%	SE49=-1.2%
j	SW49=-1%, SE49=-0.4%	SW49=-1.2%, SE49=-0.6%
k	SW49=-1%	SW49=-1.2%
l	SW49=+1%, SE49=-0.6%	SW49=+0.75%, SE49=-0.4%
m	A8IMP=+1%	A8IMP=+1.3%
n	A8IMP=-1%	A8IMP=-1.2%
o	A8IMP=+2%	A8IMP=+1.8%

Results based on benchmark fault cases delivered by engine manufacturer

Application on a Turbofan engine

SVM applied for sensor fault diagnosis

SVM	wrong estimations	score
LINEAR	640	0.0%
POLYNOMIAL	43	93.3%
SIGMOID	450	1.6%
RBF	1	99.8%

Classes Definition

- Sensors deviation: ±(1.0,2.0)%
- Health parameters deviation: (-2.5%, -1.5%, 0%, +1.5%, +2.5%)

Examined Patterns

- Sensors deviation: ±1.5%
- Health parameters deviation: (-2.5%, -1.5%, 0%, +1.5%, +2.5%)

Simulated sensor biases for all available sensors, at the simultaneous presence of component faults, where examined

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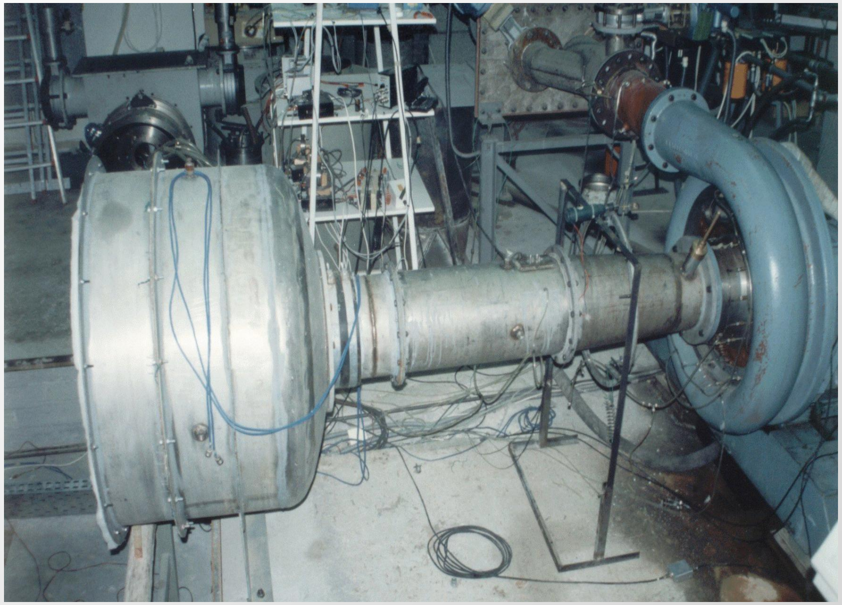
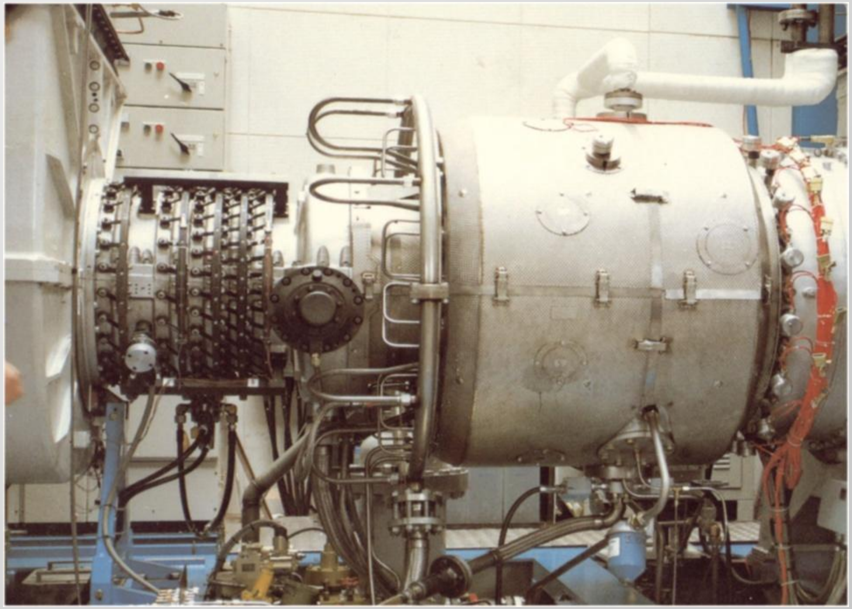
Application on compressor faults

actual implemented mechanical faults on two compressors

Radial Compressor

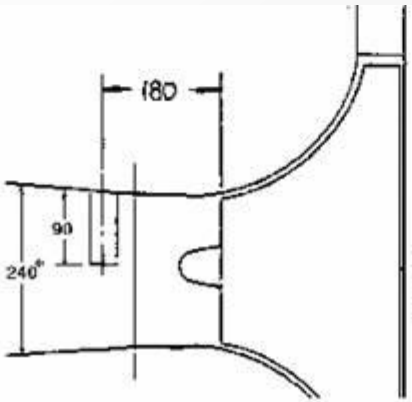


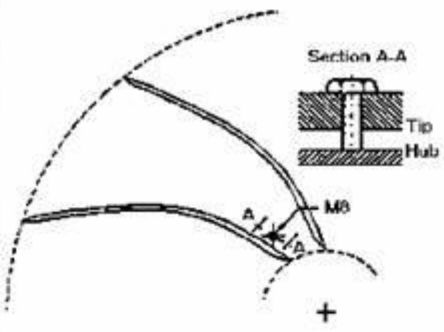
Axial Compressor



Application on compressor faults

Faults Examined: Radial Compressor





Inlet Distortion

Diffuser Fault

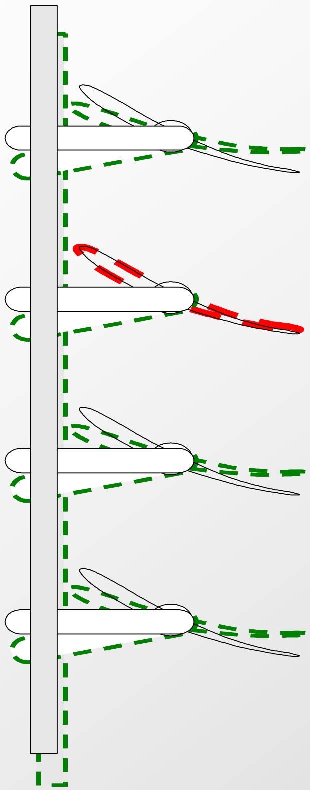
Impeller Fouling

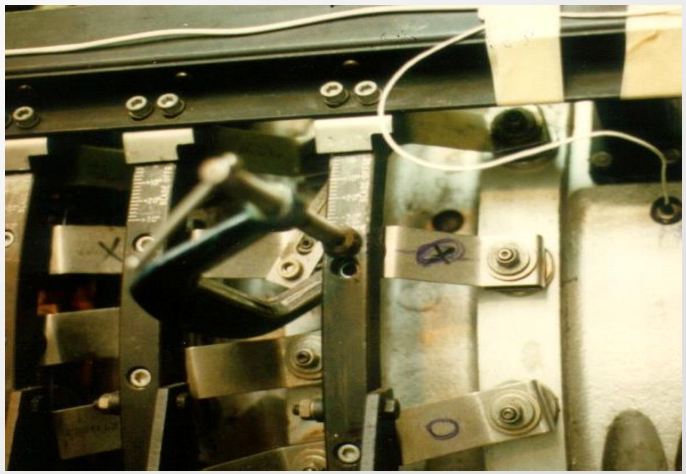
Available data consist of:

- **4 sets of 7 thermodynamic data**
- **4 sets of 1 fast response measurement**

Application on compressor faults

Faults Examined: Axial Compressor





Implemented faults:

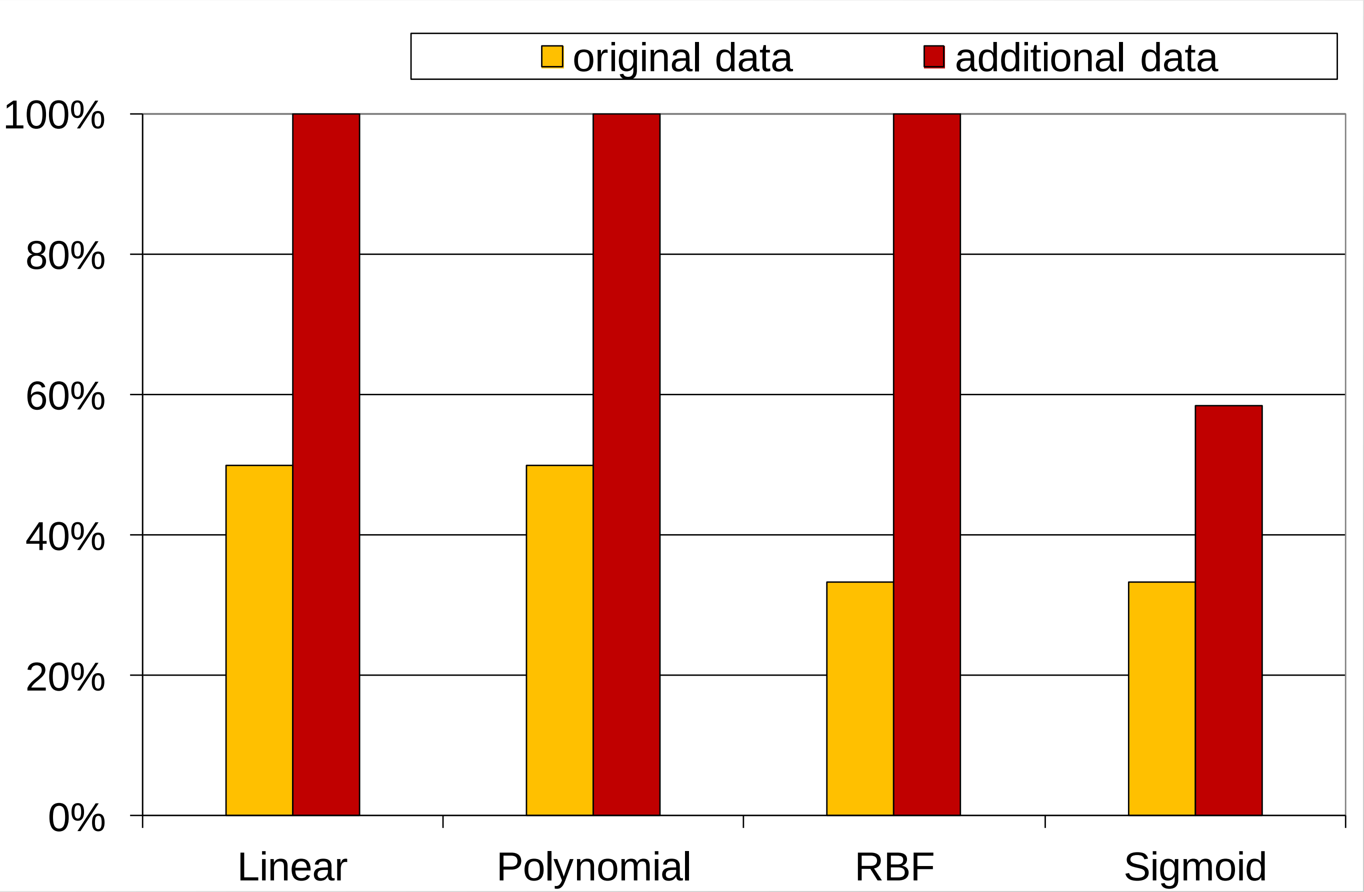
- **Fouled Rotor of Stage 2**
- **Two blades of Rotor 1 fouled**
- **Twisted blade of Rotor 1**
- **Three mistuned stator vanes**

Available data consist of:

- **4 sets of 7 thermodynamic data**
- **4 sets of 4 fast response measurements**

Application on compressor faults

results on original and additional data



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Summary - Conclusions

- **A Support Vector Machine (SVM) method, for gas turbine faults classification and diagnosis, has been presented.**
- **SVM is a well-known and efficient classification technique that in this work has been used as a stand-alone diagnostic method, supported by an Engine Performance Model.**
- **SVM efficiency has been examined through application on a number of realistic fault conditions that may encounter in practice on a gas turbine, including aerothemrodynamic faults, sensor faults and mechanical faults.**
- **The performance of SVM under all examined fault condition indicate that SVM is a powerful technique for Gas Turbine diagnosis.**