An enhanced fusion approach for fault allocation based on a limited number of measurements

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Abstract

Gas turbine maintenance is heading towards full condition based monitoring since the pressure on life cycle cost is ever increasing. Nevertheless, in currently operating machines a minimum number of measurements is used because of the associated costs and issues of reliability which are linked to any sensor. Therefore, it is an ongoing quest to define methods which are supporting the engineers in their difficult task of finding possible faulty modules or engine parts during service.

This paper suggests an improvement for the allocation of component faults for a highly under determined system in regard of the number of health parameters of a gas turbine. The estimated component faults are derived from the evaluation of a pattern recognition system in combination with a simple linear gas path analysis technique (Least Squares Algorithm) for a quasi determined system, using a linearized gas turbine model in terms of an Influence-Coefficient-Matrix (ICM). Due to the evaluations of all combinations of a quasi determined system, equal number of component performance parameters as independent measurements, a statistical evaluation of the fault identification is used. A classification procedure, depending on the available measurement, is applied to assign the estimated component fault identification into a group of secure observable component performance parameter. Furthermore, robustness in sense of wrong fault allocation due to unobservable component performance is achieved by using such a allocation procedure. The proposed technique has been applied to several simulated test cases with satisfactory results. The benefit of the presented method is that insecure fault identifications can be intercepted. The limitation of the presented method is also discussed.

NOMENCLATURE

ACRONYMS

Comp	Turbo Component
DI	Diagnostic Index
DOD	Domestic Object Damage
EPR	Engine Pressure Ratio
FCI	Fault Classification Index
$\overline{\mathrm{FI}}$	Fault Indicator
FOD	Foreign Object Damage
HPC	High Pressure Compressor
HPT	High Pressure Turbine
ICM	Influence-Coefficient-Matrix
IP	Identification Probability
LPC	Low Pressure Compressor
LPT	Low Pressure Turbine
MDI	Modified Diagnostic Index
$\overline{\mathrm{PFI}}$	Pattern Fault Indicator
PI	Pattern Indicator
RF	Realtive Frequency
SVD	Singular Value Decomposition

PARAMETERS

η_i	Efficiency of turbo component i
σ_i	Standard deviation i
w_i	Capacity of turbo component i
dis	Euclidian distance
m	Number of measurements
n	Number of health parameters
r	Correlation coefficiant
wv	Weighting value
k	Number of combinations
$\Delta\vec{x}$	Health parameter vector
$\Delta\overline{x}_i$	Sample mean i
$\Delta\vec{y}$	Measurement residual vector
Δ	Relative deviation
Σ	Singular value matrix
A8	Effective exhaust duct area in m²
G	Inverse part of the pseudoinverse
M	Measurement set
N1	Low pressure spool speed in rpm
N2	High pressure spool speed in rpm
U,V	Unitary matrices
WF	Fuel Flow
Pi, pi	Total, static pressure
Ti, ti	Total, static temperature

SUBSCRIPTS

max	Maximum

mean	Mean value
pat	Pattern
red	Reduced rank estimator matrix
ref	At reference condition
T	Transposed of a matrix
-1	Inverse of a matrix

1. INTRODUCTION

In order to optimize maintenance costs of gas turbines in service by optimizing the time between overhauls, modern monitoring systems will find a remedy. Due to the fact that gas turbines degrade over life time, monitoring systems must be capable to either identify the faulty components (Detection) or, even better to assign the changes to individual components (Diagnosis) of the gas turbine. These changes in the gas turbine can be caused by either deterioration mechanisms or by single fault events. The health of a gas turbine is represented by the deviation of the health parameters as efficiencies or mass flows from their nominal value. A schematic architecture of such a monitoring system is presented in [1] and [2].

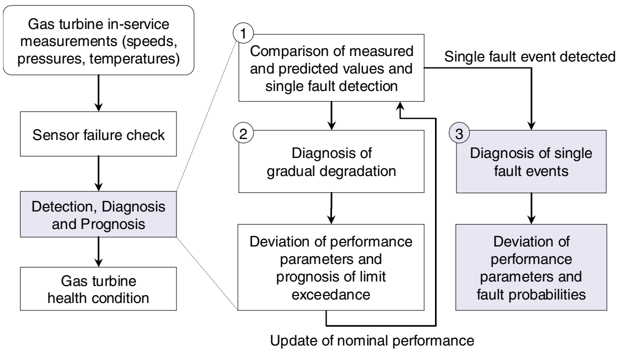

FIGURE 1. Schematic monitoring process [1]

The quality of such a monitoring process depends primarily on the available measurements and particularly on the quantity of available measurements. Nowadays, the in service instrumentations are oriented to prevent the gas turbine against major damages. For diagnostic purposes, the in service instrumentations are limited. General importance of the chosen measurement set is introduced in [3]. Hereafter the meaning of observability is mentioned to guarantee a proper health condition estimation of a gas turbine. Several authors, [4], [5] and [6], introduce mathematical decision methods which rank the quality of the instrumentation according to diagnostic purposes. The major outcome of these analyses is that the quality of either identification or diagnosis depends on the degree of the underdetermination of the systems. Several estimator approaches are introduced to overcome the problem of light and moderate underdetermined systems. To be mentioned should be also model-based or knowledge-based (rule-based) approaches. On the one hand, in order to achieve reasonable estimations, simple linearised model based least square estimators with a priori information [6] or more complex non-linear model based probabilistic examinations [7-9] are used. A different way of model-based diagnostic estimators is Kalman Filter approaches [10,11]. Non-linear optimization approaches with proper constrains [12] are also auspicious. On the other hand knowledge-based approaches as a fuzzy-logic based estimators with a diagnosis probability value are introduced for moderate underdetermined systems in [1]. Another field of fault detection and diagnosis approaches is that pattern recognition [13] and of neural networks. Especially Probabilistic Neural Networks as proposed in [14-16] are successfully applied. For a highly underdetermined system, a quantitative prediction of the faulty health parameter is getting worse. To find a remedy, it will help to identify a fault in a particular partition of a gas turbine without a quantitative prediction but with a reliable identification. This paper introduces a fusion of two well known methods to identify and allocate faults with highly underdetermined systems. The fault identification is concentrated to single fault events and can be attached to box three in Fig. 1. The method can be interpreted as a back up method for a monitoring process in case of several measurements are no longer available for single fault diagnostic purposes during gas turbine life time.

2. GAS TURBINE CONFIGURATION USED

The used gas turbine is characterized by a bypass and a two spool system. The reason for this choice of a gas turbine is that it represents an application for today's aviation as well as an application for an industrial gas turbine. The gas turbine consists of an inlet, five turbo components (FAN, LPC, HPC, HPT and LPT), a mixer and an exhaust duct (DUCT). The configuration and the station numbering can be seen in Fig. 2.

The station numbering of the thermodynamical planes is according to international standard.

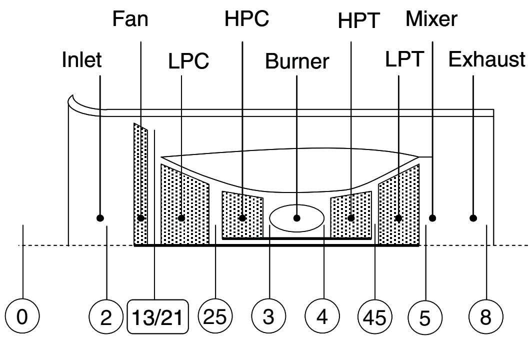

FIGURE 2. Gas turbine nomenclature

The health status of each turbo component is stated by the deviation of its performance parameters "capacity" and "efficiency" from their nominal values. Except the health status of the exhaust duct is stated by the deviation of its effective area from its nominal value. Thus, a total number of health parameters is n=11 in this particular example (Fig 2). The deviations of performance parameters from their nominal values are defined in percent as follows:

(1) $\Delta\eta_i = (\eta_i - \eta_{i,ref}) \cdot 100\%$

(2) $\Delta w_i = \left(\left(w_i \cdot \sqrt{T_i} / p_i\right) / \left(w_i \cdot \sqrt{T_i} / p_i\right)_{ref} - 1\right) \cdot 100\%$

(3) $\Delta A_8 = \left(\left(A_8 / A_{8,ref}\right) - 1\right) \cdot 100\%$.

2.1. Instrumentation

A typical in-service instrumentation of a gas turbine consists of spool speeds, fuel flow and several pressures and temperatures. For a general investigation in this paper a pool of possible measurements is presented. The following table contains the set of independent measurements, as used in this paper, describing the operating point.

No.	*Description*	*Symbol*	*Unit*
1	Engine Pressure Ratio	EPR	-
2	Ambient temp.	t0	K
3	Ambient pressure	p0	kPa

TAB 1. List of independent measurements

The EPR is the rating parameter representing the power setting. Ambient pressure and ambient temperature are referred to the operating conditions. Available dependent measurements for the investigation in this paper are presented in Table 2. For more realistic data, measurement noise [9] is added to the simulated raw measurement data. Not known standard deviations are assumed to be in the same size as measurements in comparable thermodynamic locations.

No.	*Description*	*Symbol*	*Unit*	3σ
1	Burner fuel flow	WF	kg/s	0.002
2	Low spool speed	N1	RPM	6
3	High spool speed	N2	RPM	12
4	Fan inner temp.	T25	K	2
5	HPC exit temp.	T3	K	2
6	LPT exit temp.	T5	K	2
7	Fan outlet pressure	P13	kPa	0.3
8	Fan inner pressure	P25	kPa	0.4
9	HPC exit pressure	P3	kPa	5

TAB 2. List of dependent measurements

For further investigations, some combinations out of Table 2 are used as a representative set of a degraded “in-service” instrumentation.

3. THE LINEAR MODEL APPROACH

As one of the simplest approaches for describing the gas turbine, the linear gas path model approach is chosen. A briefly introduction to the well known method is presented. The simplest mathematical description of the relations between the change in health parameters of the gas turbine $\Delta\vec{x}$ and the change in measurable parameters $\Delta\vec{y}$ is:

(4) $\Delta\vec{y} = ICM \cdot \Delta\vec{x}$ with $\Delta x_i = \dfrac{x_i - x_{ref}}{x_{ref}}$.

The ICM implies the physical relations between the two vector sets in a predefined operating point. For a proper estimation of the gas turbine health parameters out of the known measurements, the inverse of the ICM must be calculated.

(5) $\Delta\vec{x} = ICM^{-1} \cdot \Delta\vec{y}$

For a determined system (equal number of known measurements and unknown health parameters) a unique solution is available. For a real application, where the number of available measurements is less than the unknown health parameters, a modification of equation (5) is necessary. In equation (6) the Moore-Penrose inverse of the ICM for underdetermined systems is presented as a frequently used estimator for diagnosis purposes.

(6) $\Delta\vec{x} = (ICM^T \cdot ICM)^{-1} \cdot ICM^T \cdot \Delta\vec{y}$

4. ROBUST FAULT IDENTIFICATION USING A MODIFIED DIAGNOSTIC INDEX (MDI)

Due to the fact, that the real problem is underdetermined, equation (6) gives an estimation of the gas turbine health parameters in a least square estimation sense. Observability problems as a consequence of lack of information make a proper estimation of health parameters difficult for highly underdetermined systems. Investigations show an inability of such algorithms to achieve proper fault magnitude estimations. Furthermore, the actual fault can be attributed to other health parameters. In a first step the idea of the Diagnostic Index (DI) as proposed in [8] and [9] is used.

(7) $DI = \dfrac{\left|\Delta\overline{x}_i\right|}{\sigma_{\overline{x}_i}}$ with $\Delta\overline{x}_i = \dfrac{1}{k} \cdot \sum_{j=1}^{j=k} \Delta x_{i,k}$

Where $\Delta\overline{x}_i$ is the mean value and $\sigma_{\overline{x}_i}$ the standard deviation for a health parameter $\Delta\overline{x}_i$. In order to achieve a reasonable estimation of the fault identification, a combination of determined systems (m=n) must be chosen as many time as

$$\text{(8)} \qquad \text{Number of combinations (k)} = \binom{n}{m}.$$

Based on a gas turbine with n=11 health parameters, the number of combinations are summarized in Table 3 according to the number of available measurements m.

No. of measurements m	*9*	*8*	*7*	*…*
Number of combinations k	55	165	330	…

TAB 3. Number of combinations

The needed values for equation (7) are obtained in a further step. A reduced order estimator in means of a singular value decomposition can be used as in [17]. A different application of the method is presented in this paper. To increase the numerical robustness of equation (6) the full rank matrix expression out of the Moore-Penrose inverse

$$\text{(9)} \qquad G = (ICM^T \cdot ICM)$$

is replaced by a reduced rank matrix G_{red} which is a result of a singular value modification as follows:

$$\text{(10)} \qquad G = U \Sigma V^T,$$

where the smallest singular value in Σ is removed. The new and robust estimator for a determined system is hereafter:

$$\text{(11)} \qquad \Delta\tilde{\tilde{x}} = G_{red}^{-1} \cdot ICM^T \cdot \Delta\vec{y}$$

The benefit is displayed in Fig. 3. Uncertainties, represented by the standard deviation σ, caused by numerical uncertainties of the estimation are minimized. The standard deviations of the health parameters are obtained by the evaluation of the estimator for all combinations out of equation (8).

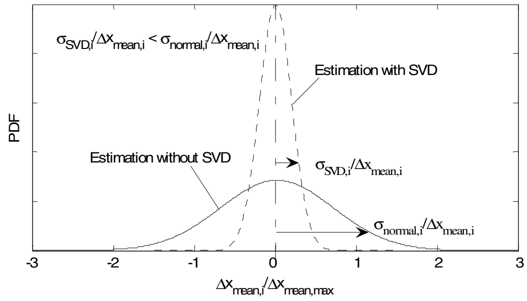

FIGURE 3. Improvement of the estimation with a MDI

Due to the modification of the estimator, the evaluation of the diagnostic index has shown an encouraging result of the fault identification for highly underdetermined systems. The highest amplitude of DI is assigned to one of the gas turbine's main components in which the affected health parameter is assumed. The right identification of the fault suffered health parameter is still limited by the lack of observability. Experiences show a satisfactory result by the identification of the faulty health parameter into a right turbo component of the gas turbine. Consequently, a fault classification is to be split into major gas turbine partitions represented by the turbo components itself. For all the following identification approaches, the fault identification is based on the turbo component level. As introduced by [9], a turbo component diagnostic index for the DI approach can be formulated as:

$$\text{(12)} \qquad DI_{Comp} = \sqrt{DI_\eta^2 + DI_w^2}$$

The improved success rate for the fault identification in turbo components is shown in Table 4 and is summarized for the compressor and turbine part. The investigation is carried out with a simulated in-service instrumentation with a moderate under determination of the system for generic fault data. An improvement of about thirty percent could be expected. The improvement itself is mainly dependent on the available instrumentation.

Method	*Compressor*	*Turbine*
Estimation without SVD	66%	73%
Estimation with SVD	96%	95%

TAB 4. Improvement of the success rate

5. GEOMETRICAL PATTERN RECOGNITION

As a second identification method of a faulty component, an engine-model independent approach is chosen. According to [13], a pattern recognition approach based on a geometrical comparison of measurement signatures is implemented. A set of generated training patterns consisting of measurement signatures derived by a non-linear engine model are summarized in Appendix A which reflects possible faults in all combinations. These faults are representative for foreign object or domestic object damages (FOD/DOD) which are characteristic single event faults. The task for pattern recognition is to find the right faulty component out of the training pattern of measurements according to the actual measured measurement signature. For that purpose the correlation (equation 13) between the training measurement patterns and the measured measurement signature is calculated and the corresponding Euclidian norm (equation 14) is computed. These two terms reflect the quantitative and the shape similarity of the derived measurement signature $\Delta\vec{y}$ to the pattern signatures $\Delta\vec{y}_{pat}$.

(13) $$r = \frac{\sum_{i=1}^{m}(\Delta\vec{y}_i - \Delta\bar{y})\cdot(\Delta\vec{y}_{pat,i} - \Delta\bar{y}_{pat})}{\sqrt{\sum_{i=1}^{m}(\Delta\vec{y}_i - \Delta\bar{y})^2 \cdot \sum_{i=1}^{m}(\Delta\vec{y}_{pat,i} - \Delta\bar{y}_{pat})^2}}$$

(14) $$dis = \sqrt{\frac{1}{m}\cdot\sum_{i=1}^{m}(\Delta\vec{y}_i - \Delta\vec{y}_{pat,i})^2}$$

The correlation r ranges between the values -1 to 1 and has a value of 1 for a strong similarity between the measured and the training measurement. The Euclidian norm has a value of 0, if the measured and a known measurement pattern $\Delta\vec{y}_{pat,i}$ are similar.

In accordance to [13], all correlations and Euclidian norms are calculated for the measured measurement and the measurement patterns for all known fault cases. The obtained values are concentrated into the Fault Classification Index FCI as follows for each fault case i:

(15) $$FCI_i = \sqrt{(dis_i^2 + (1-r_i)^2)}\ .$$

A value of FCI near 0 indicates that the measured measurement signature is geometrically similar or close to similarity to a known fault measurement signature out of the pool of training measurement patterns. In case of the fact, that during operation of the engine one or more sensors were out of function, some measurement signatures can become similar to different fault cases as illustrated in Fig. 4. The lost of a sensor is marked with a cross in the measurement signature.

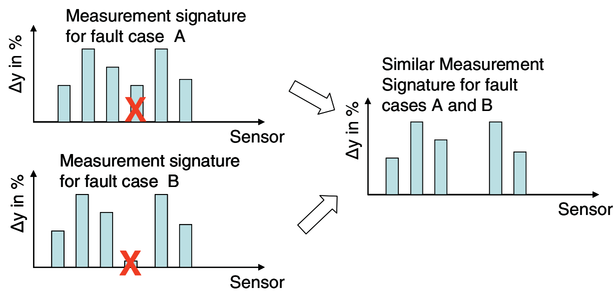

FIGURE 4. Measurement signatures after sensor lost

In case of an underdetermined system (less number of known measurements as unknown health parameters), the degree of observibility is decreasing. A proper identification of the fault, either A or B becomes difficult to differ especially if measurement noise is present. To overcome the problem of ambiguousness faults, ten percent of the lowest FCI's are taken into account to identify the most likely faulty component or component combination. In a first step, a relative FCI is calculated for the best ten percent of the estimations:

(16) $$FCI_{rel} = \frac{FCI_i}{FCI_{max}}\ ,$$

where FCI_{max} is the highest Fault Classification Index out of the ten percent of the best FCI. In a second step a weighting function (equation 17) is used to weight the turbo component involved in all fault cases corresponding to the chosen best FCI_{rel}.

(17) $$wv_i = -\tanh\left((FCI_{rel} + 0.22)\square 2\right) + 1$$
$$\text{with } 0 \le FCI_{rel} \le 1$$

A hyperbolic tangent is chosen as a weighting function due to the fact that the lowest FCI_{rel} must not correspond to the right fault case due to poor observability. For that reason a smooth weighting of the lower FCI_{rel} is chosen.

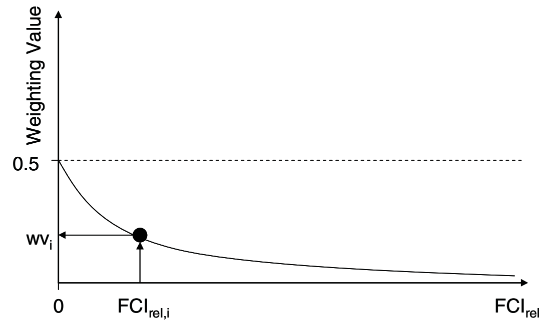

FIGURE 5. Weighting function

As result, a pattern indicator PI is calculated for each turbo component out of the training patterns according to equation (18).

(18) $$PI_i = \sum_{j=1}^{b} wv_j \cdot FCI_{rel,j}^{=g} - \sum_{j=1}^{b} wv_j \cdot FCI_{rel,j}^{\neq g}$$

The index i for PI represents the faulty turbo component i. Parameter b is the number of the ten percent best choices of faults as discussed earlier. The first sum term in equation (18) represents the weighted sum of FCI corresponding to fault case g, the second term is representing the weighted sums of FCI not corresponding to fault case g. The turbo component with the highest PI is the most probable fault case among all and is chosen as the best estimation. An output vector called Pattern Fault Indicator ($\overrightarrow{PFI}$) is defined which relates a PI to the corresponding turbo component.

(19) $$\overrightarrow{PFI} = [PI_1, PI_2, \ldots.., PI_z]$$

6. IDENTIFICATION FUSION APPROACH

After examining the two presented identification approaches, two fault estimation vectors are obtained. If a high under determination of the system in regard of the health parameters is present, the obtained estimated results must not be similar. In presence of measurement noise, coupled with a not sufficient quantity of measured snapshots for a proper averaging of the measured data the fault estimation becomes difficult. To overcome this problem, an Identification Probability (IP) for the faulty components will be calculated.

A fuzzy logic approach with a fuzzy response surface is chosen. Knowledge based weighting of each component of the obtained fault estimation vectors out of the modified diagnostic indexing and the geometrical pattern recognition for underdetermined systems is implemented.

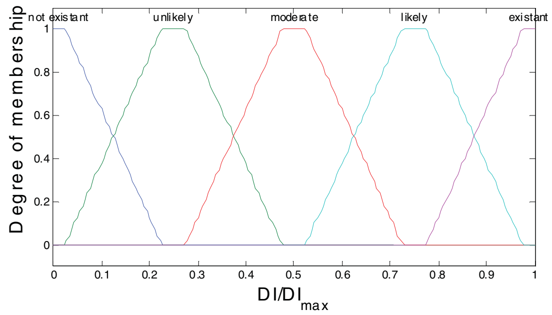

FIGURE 6. Representative membership function

The classification of the obtained estimations of faulty components is presented in Fig. 6 in the membership function. For both, identification approaches and for the output, similar membership functions are used. Except of the decision rules, summarized in Appendix B creates the non symmetrical fuzzy response surface as illustrated in Fig. 7 for the IP.

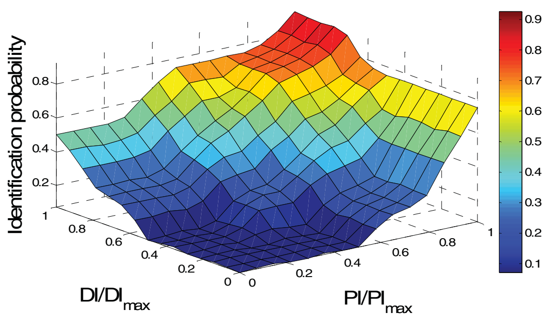

FIGURE 7. Fuzzy response surface for the Identification Probability

Each turbo component obtains an IP between 0 (not existent in a fault) and 1 (existent in a fault) after examining the fuzzy decision rules. Turbo components with an IP>0.5 are regarded as involved in the fault. For further investigation, a fault indicator vector is created with the chosen turbo component put to 1 if estimated as faulty if IP_i>0.5. Else, the turbo component receives the value 0.

$$\begin{aligned} &\vec{FI} = [Comp_1, Comp_2, ..., Comp_z] \\ &\text{if} \quad IP_{Comp,i} > 0.5 \text{ then } Comp_i = 1 \\ &\text{else } Comp_i = 0 \end{aligned} \tag{20}$$

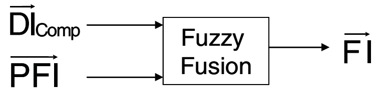

FIGURE 8. Schematic fusion of the obtained faulty component estimations

7. SIMPLIFICATION OF THE ENGINE INTO OBSERVABLE PARTS

In regard of underdetermined systems, not observable combinations of component faults represented by the health parameters are present. These faults are attributed to other, in real case not from the fault affected health parameters. To avoid wrong fault allocations by the fault identification through the previous described estimators, either the number of instrumentation must be increased or unobservable or poor observeable turbo components must be jointed to an observable block. To achieve the second aim a pattern search is realised between the training measurement patterns. A similar mathematical approach is taken as in equation (15) applied. Fault cases out of the training measurement patterns are searched which have a strong similarity in the measurement signatures to each other.

A conservative interpretation is used for the choice of jointing the turbo component to an observable block. Correlation coefficients higher than $r_i \geq 0.8$ are treated as a high correlation between fault measurement signatures and a Euclidean norm lower than $dis_i \leq 0.45$ is treated as shape similar. As a result, an upper limit of $FCI_i \leq 0.5$ is obtained which indicates that a pair of fault cases cannot be distinguished. Applied this approach between all training measurement signatures, a symmetrical matrix A is obtained with all FCIs of the examined pattern faults d.

$$A = \begin{pmatrix} FCI_{11} & \cdots & FCI_{1d} \\ \vdots & \ddots & \vdots \\ FCI_{d1} & \cdots & FCI_{dd} \end{pmatrix} \tag{21}$$

To obtain the turbo components for jointing into an observable block, matrix A is sorted by fault types as for example FAN, LPC, HPC etc. faults and their combinations. The indication of unobservabilty between the fault types is derived by the relative frequency how often the FCI value between two fault types is under the upper threshold as defined earlier.

$$RF_{Fault\ a,b} = \left(\frac{\text{Number of FCI} \leq 0.5}{\text{Total Number of FCI}} \right)_{Fault\ a,b} \tag{22}$$

For $RF_{Fault\ a,b} \geq 0.5$, the in the fault involved turbo components are jointed. For some chosen instrumentation sets (Appendix C), the obtained observable blocks are summarized in Fig. 9.

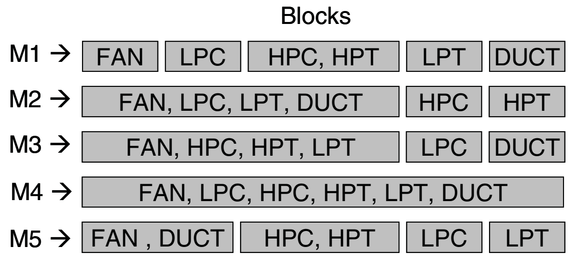

FIGURE 9. Simplified observable gas turbine blocks derived by the chosen instrumentation

8. APPLICATION OF THE INTRODUCED FAULT IDENTIFICATION APPROACH

To investigate the robustness against wrong fault allocations of the fault identification and allocation approach as described, a generic fault is simulated. The identification of the fault is conducted with the presented instrumentation sets. The implemented fault is a combination of HPC and HPT faults as follows:

$$\Delta\eta_{HPC} = -1.4\%,\ \Delta w_{HPT} = -1.3\%.$$

Following figures (Fig. 10 and Fig. 11) show the allocation of the fault derived by the presented approach with the instrumentation set M1. The fault identification derived by the model independent pattern search indicates an obvious fault in the HPC part ($PFI_{HPC} \approx 70\%$) and an unsecure fault in the HPT part ($PFI_{HPT} \approx 55\%$). The model based identification approach delivers for the same fault an secure identification of the fault in the HPC part ($DI_{HPC} = 100\%$), but the second involved turbo component is not identified as faulty ($DI_{HPT} \approx 20\%$). That misidentification is related with a poorer performance of the model based estimator handling with highly underdetermined systems in regard of health parameters and noisy data. For other fault cases the pattern recognition estimator can lead to a misidentification of a fault affected through observability problems. A secure indicator for a faulty component is derived by the fusion of both estimators as shown in Fig. 11. for the HPC component.

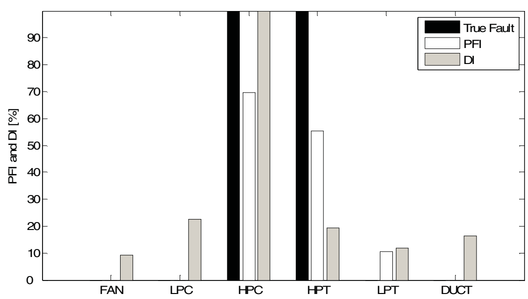

FIGURE 10. Fault identification investigated by the identification approaches (M1)

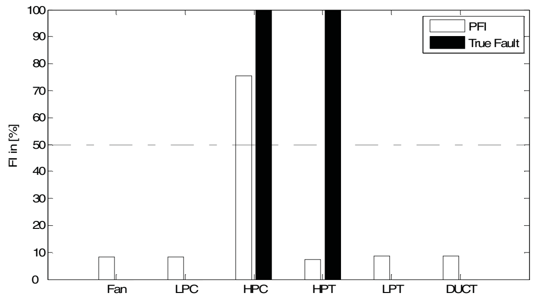

FIGURE 11. Fault indicator derived out of the fusion of the obtained identification estimations (M1)

The derived fault indicator is allocated into the secure observable block out of the simplification approach previously described. The effected block is highlighted white in Fig. 12. The information for maintenance personal is a secure allocation of the faulty components.

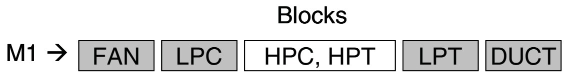

FIGURE 12. Faulty gas turbine block recommendation

The result has to understand as a secure recommendation of the faulty block. The allocation of the fault by other instrumentation sets is summarized in Fig. 14. To point out the necessity of the fusion approach with a fault allocation is shown by the same fault executed with instrumentation set M4.

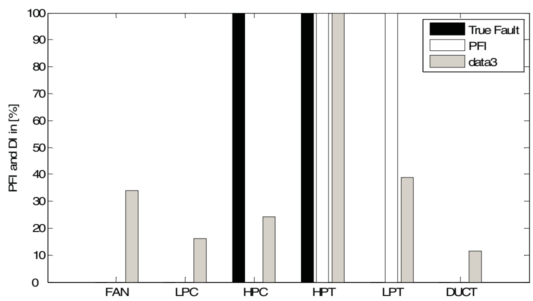

FIGURE 13. Fault identification investigated by the identification approaches (M4)

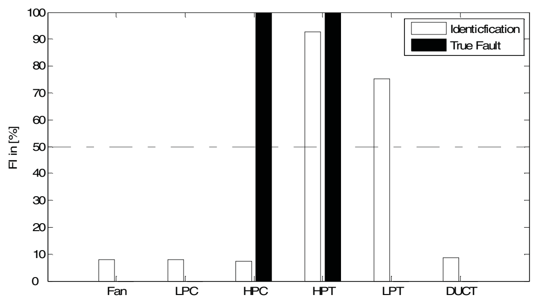

FIGURE 14. Fault indicator derived out of the fusion of the obtained identification estimations (M4)

In that case it is obvious that the pattern search alone would leave to a misidentification. The fact that the chosen instrumentation set is poor for fault identification purposes is obvious by comparing the obtained observability block for M4 in regard to others (Fig. 9). There is no secure resolution of turbo components possible. As result, the whole gas turbine block is highlighted white (Fig.15) and no additional information about the fault is obtained.

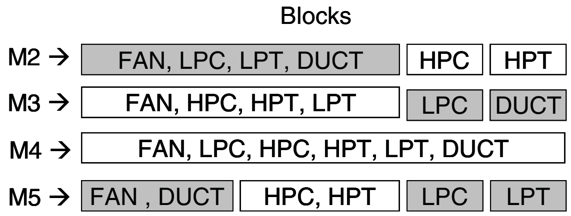

FIGURE 15. Faulty gas turbine block recommendation

9. CONCLUSION

A way of indentifying a fault in a particular block of a gas turbine, using a fusion of a model-based least square estimator and a pattern search technique has been presented. It has to be pointed out, that the presented method is capable to allocate a fault in a predefined block with a minimum of measurements. A major benefit is that a secure allocation has been created by the fusion of the different methods. Wrong fault allocations derived by one of the estimators can be reduced through a fusion of different based estimator approaches. Furthermore, robustness against observability problems for highly underdetermined systems is achieved. The presented method of fault allocations can be interpreted as a back up algorithm in a health monitoring system with sophisticated detection and diagnostic tools which deals with moderate underdetermined systems. In cases where measurements are lost, a roughly estimation of the fault location is still assured.

10. ACKNOWLEDGMENTS

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11. LITERATURLISTE

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APPENDIX A: TRAINING MEASUREMENT PATTERN

To achieve proper pattern recognition, a fair assortment of possible gas turbine conditions should be chosen. For the test case in this paper, a gas turbine with n=11 health parameters is chosen, represented by the efficiencies and flow factors which are deviated from their nominal value. In Table 5 a schematic summarization of the used fault patterns are shown. To roughly cover all possible FOD / DOD faults, all combinations of health parameter deviations are simulated, started with one health parameter until all health parameters of two turbo components are deviated in 1% steps in the range of 0% to -2%.

Affected health parameter	*Simulated deviations*
$\Delta\eta_{LPC}$	-(0,1,2)
Δw_{LPC}	-(0,1,2)
$\Delta\eta_{IPC}$	-(0,1,2)
.	.
.	.
$\Delta\eta_{HPT}$	$-(0,1,2)$
.	.
.	.
$\Delta\eta_{LPC}, \Delta w_{LPC}$	All combinations of $\Delta\eta_{LPC} = -(0,1,2)$ $\Delta w_{LPC} = -(0,1,2)$
.	.
.	.
$\Delta\eta_{HPT}, \Delta w_{HPT}$	All combinations of $\Delta\eta_{HPT} = -(0,1,2)$ $\Delta w_{HPT} = -(0,1,2)$
.	.
.	.
$\Delta\eta_{LPC}, \Delta\eta_{IPC}, \Delta\eta_{HPC}$	All combinations of $\Delta\eta_{LPC} = -(0,1,2)$ $\Delta\eta_{IPC} = -(0,1,2)$ $\Delta\eta_{HPC} = -(0,1,2)$
.	.
.	.
.	.

TAB 5. Schematic health parameter deviation for a bench of training vectors

The measurement patterns are derived with the help of a commercial non linear gas turbine performance tool by calculating a synthesis.

APPENDIX B: FUZZY RULES

The performed fusion rules for the obtained fault identifications out of the independent fault identifications estimators are presented in Table 6.

If $\overrightarrow{PFI}$	*And* $\overrightarrow{DI}_{Comp}$	*Consequence*
1	1	1
1	2	1
1	3	1
1	4	2
1	5	3
2	1	1
2	2	1
2	3	1
2	4	3
2	5	2
3	1	1
3	2	1
3	3	2
3	4	3
3	5	4
4	1	2
4	2	2
4	3	3
4	4	4
4	5	4
5	1	4
5	2	4
5	3	4
5	4	5
5	5	5

TAB 6. Fuzzy decision rules

Indexing is as followed: 1 = not existent; 2 = unlikely; 3 = moderate; 4 = likely; 5 = existent.

APPENDIX C: INSTRUMENTATION SETS

To have a meaningful result of the method application, 5 different instrumentation sets out of the available instrumentations are chosen. The chosen amount of available measurements is variable. Hence, the system is up to several times underdetermined in respect to the amount of health parameters and turbo components.

	1	*2*	*3*	*4*	*5*	*6*
M1	N1	N2	WF	P25	T3	T5
M2	N1	N2	P3	T3	T5	-
M3	WF	P13	T25	P3	T5	-
M4	N1	WF	T3	T5	-	-
M5	N2	WF	T25	T5	-	-

TAB 7. Chosen representative instrumentation sets

Herein, M1-M5 stands for the 5 different investigated measurement sets as representatives. The measurements are noisy and therefore a simple noise filter is implemented. One filtered reading is achieved by an averaging of ten unfiltered measurements. In other words, to receive a filtered measurement signature, ten raw snapshots will be averaged. In this investigation the first filtered reading after ten snapshots is used.