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Gas Path Analysis Of Two Shaft Gas Turbine Engine By Utilizing Multi Operating Point Conditions And Bank Of Kalman Filters

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Abstract

One of the main purposes of gas path analysis (GPA) in gas turbine industry is to evaluate the health conditions of gas turbine engine components. In this study, a GPA module has been developed to compare all health parameters of a compressor of a specific gas turbine engine such as flow capacity, efficiency and pressure drop with respect to the reference values from a healthy engine. Health parameters' deviations from their reference values (due to engine degradation) are then evaluated based on measured gas path parameters in multiple operating points. The GPA module operates as a developed computer-based simulator model which receives operating point parameters as inputs. The performance behavior of a healthy engine at the specified operating conditions is generated by the simulator as the model outputs. A set of these outputs is compared with the corresponding actual turbine outputs received by sensors embedded on the turbine. In case of differences between the simulator outputs and actual sensor data, model health parameters are changed by an estimator whose algorithm is based on an Unscented Kalman Filter (UKF), so that the evaluated parameters and their corresponding sensor data coincide. It has been proved that a certain number of health parameters could be ignored in order to optimize the GPA module overall performance. The developed GPA module encompasses different scenarios for the engine model in each of which the number of health parameters varies with a single Kalman Filter (KF) estimator attributed to each model. The combination of KFs constitutes a bank of KF. The results show the effectiveness of bank of KF utilization in health parameter fault estimation for some case studies performed on the studied gas turbine. It has also been shown that fault estimation algorithm is enhanced by employing multiple operating points. The results have been verified utilizing a GPA module developed and implemented on a Gas Turbine engine.

Keywords: gas path analysis, gas turbine, fault diagnosis, health parameters

1. Introduction

One of the most important issues in gas turbine fault detection process is the performance analysis of gas turbine engines. Fouling, corrosion and tip clearance are the common faults which affect the efficiency and flow rate of the engine components. By measuring and analyzing the engine performance parameters such as rotational speeds, temperature, pressure, etc., these faults could be detected (Urban et al., 1975).

Among the numerous approaches for gas turbine condition monitoring, Gas Path Analysis (GPA), as a performance-analysis-based approach, is one of the most effective and powerful tools. The GPA approach provides valuable information regarding the deterioration of individual gas turbine engine components by estimating the deviation of the engine health parameters such as flow rates and efficiencies of the engine components (Liu et al., 2011). As gas turbine health parameters deviate from their nominal values which correspond to the healthy engine, the performance degradation occur in the components.

The GPA approach was utilized for the first time by Urban et al. (1967) and the inclusion of engine nonlinearities in the GPA was first introduced by Stamatis et al. (1990). Barwell et al. (1987) and Doel et al. (1994) presented other fault diagnostic methods. In addition, operational improvements in the model-based fault diagnostic techniques have been introduced by (Panov et al., 2013). On the other hand, many integrated GPA methods have been developed using weighted-least-squares-based method (Doel et al., 1993), Bayesian (Pu et al., 2013) and artificial neural networks (Ghafir et al., 2014) genetic algorithm (Wallin et al.;2004) and fuzzy systems (Verma et al.;2006). Utilization of Kalman-based observers is another common solution in the GPA approach as reported (Volponi et al., 2003; Kobayashi et al., 2003) for linear and by (Kobayashi et al., 2005; Dewallef et al., 2003) for nonlinear systems. A different error estimation approach for the fuel controller of a power generating gas turbine engine has also been introduced in (Montazeri et al, 2017) while (Tsoutsanis et al., 2023) investigated performance diagnostics.

In this study, the health parameters for a two-shaft gas turbine engine are estimated based on Kalman filter (KF) technique as a basis for fault detection process. The estimation is essential for predictive troubleshooting of the engine and is based on the operating points of the engine.

2. Data and methods

2.1. System description

In this study, component health conditions are evaluated by the GPA approach. An engine model (GT model) calculates the engine parameters based on the environment conditions measured by the sensors and the health parameters estimated by the estimation algorithm (Kalman Filter). These calculated parameters are then compared with the corresponding parameters, evaluated by a healthy gas turbine engine model (GT Healthy). This healthy model is the same as the GT model except that its health parameters have been set to zero. The health parameters are the efficiency and mass flow deviation of the engine components from its healthy conditions which will be discussed in more detail. The difference between the GT Model output (Out_Real) and the GT healthy output (Out_Healthy) is forwarded to the Kalman filter for health parameters estimation so that the GT model outputs become as close as possible to the corresponding Healthy engine parameters. This process is repeated to obtain until the best estimation which will lead to the lowest error signal. The schematic diagram of the GPA algorithm is illustrated in Figure 1.

The proposed GPA method operates as a developed computer-based simulator model. The operating point parameters are considered as the input data (ambient conditions) which are: compressor inlet pressure ($\mathrm{P_{InComp}}$), compressor inlet temperature (T_{InComp}), power turbine speed (NPT), compressor outlet pressure (P_{OutComp}) and ambient relative humidity (RH). This set of inputs has been designated by vector **V**.

$$\mathbf{V} = \begin{bmatrix} T_{\mathrm{InComp}} \\ \mathrm{P_{InComp}} \\ \mathrm{NPT} \\ \mathrm{RH} \\ P_{\mathrm{OutComp}} \end{bmatrix} \tag{1}$$

The performance parameters of the engine, generated by the engine model are the gas generator shaft speed (NGG), gas turbine exhaust temperature (TET), compressor outlet pressure ($\mathrm{P_{OutComp}}$) and compressor outlet temperature ($\mathrm{T_{OutComp}}$) which are designated by vector Out.

$$\mathbf{Out} = \begin{bmatrix} TET \\ \mathrm{P_{OutComp}} \\ \mathrm{NGG} \\ \mathrm{T_{OutComp}} \end{bmatrix} \tag{2}$$

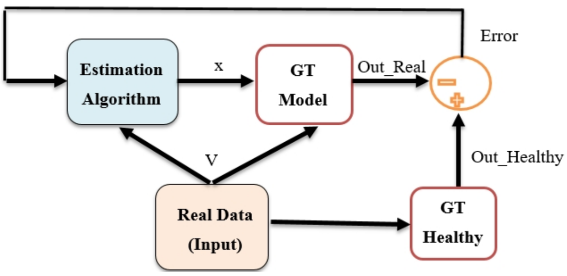


Fig. 1. The schematic diagram of the GPA algorithm.

These calculated parameters are compared with the corresponding actual turbine outputs (measurements). In case of differences between the z vectors of the simulator and the actual turbine data, an estimator changes the health parameters (vector X) of the model so that model outputs coincide with the output of the actual turbine.

The estimator algorithm is based on an UKF procedure which estimates the turbine health parameters deviations from the healthy conditions. Therefore it is needed to define the reference health parameters for the engine model (X_d). For this purpose, the engine model is divided into five sections which are: compressor, 1st stage of the gas generator turbine (GG), 2nd stage of the gas generator turbine, 1st stage of the power turbine (PT) and 2nd stage of the power turbine. For each section, three health parameters are defined as: mass flow rate, pressure loss and efficiency. Thus there will be the total of 15 health parameters.

The GPA health parameter estimation algorithm is represented as a block model in Figure 2. The detailed fault diagnostic estimation by UKF is as follows:

$$\mathbf{x} = \begin{bmatrix} \Delta\dot{m}_{comp} \\ \Delta\eta_{comp} \\ \Delta P_{comp} \\ \Delta\dot{m}_{GG-1st\ stage} \\ \Delta\dot{m}_{GG-2nd\ stage} \\ \Delta\dot{m}_{PT-1st\ stage} \\ \Delta\dot{m}_{PT-2nd\ stage} \\ \Delta\eta_{GG-1st\ stage} \\ \Delta\eta_{GG-2nd\ stage} \\ \Delta\eta_{PT-1st\ stage} \\ \Delta\eta_{PT-2nd\ stage} \\ \Delta P_{GG-1st\ stage} \\ \Delta P_{GG-2nd\ stage} \\ \Delta P_{PT-1st\ stage} \\ \Delta P_{PT-2nd\ stage} \end{bmatrix} \tag{3}$$

The ambient conditions along with NPT are first fed into the engine model and the UKF. The engine model calculates many outputs from which, four are forwarded as another set of inputs to the UKF. These signals are: NGG, T_7, P_3 , T_3 (vector Z). Finally the UKF estimates the map shifts (heath parameter deviations) that are generated for every health parameter with respect to their corresponding healthy conditions. These map shifts are called symptoms and are designated by a 15 element vector. If these map shifts are sufficiently small, then there will be no fault in the engine. Otherwise, every rather large symptom corresponds to a fault in some part of the engine. The 15 symptoms are the deviation of mass flow, efficiency and pressure loss in the compressor, first and second stage of the gas generator turbine and first and second stage of the power turbine. At first these map shifts have to be tuned. In other words, data from a healthy gas turbine is forwarded to the UKF and engine model and a vector of symptoms is generated. This map shift is then used as a permanent map shift for the rest of the analysis because it is the difference between the healthy gas turbine and the engine model that does not have to exist ideally. Therefore this undesired deviation between the model and the healthy engine is accounted for by this initial map shift. Every other deviation of the symptoms from this initial map shift is then considered as the engine fault.

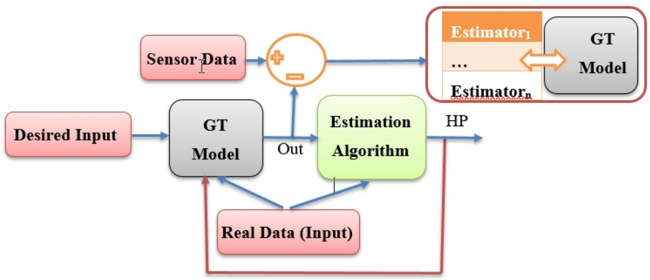


Fig. 2. Schematics of the Kalman filter and engine model interaction.

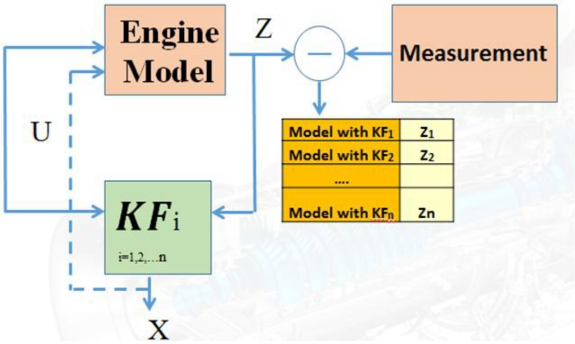


Fig. 3. Bank of KFs interactions with the model.

The use of all health parameters in the estimation process has some disadvantages the most serious of which is the smearing effect. This means that even healthy parameters may be estimated to be faulty. For this reason, a set of X vectors are assumed in each of which a certain number of health parameters are permitted to vary and the rest are assumed to be fixed. The utilization of a single KF for each set of health parameters is then applied. The combination of these KFs constitutes a bank of KF. The multiple estimation resulting from the bank of KF estimation algorithm are analyzed in order to detect the heath parameter deviations. The GPA health parameter estimation algorithm with the use of bank of KFs is illustrated in Figure 3. In this figure, for each set of heath parameters, a single KF_i, $i = 1,2,\ldots,n$, (where n is the numbers of health parameters sets) is attributed which estimates an output vector Zi. The estimated parameter is then compared with the real corresponding data from IGT25 measurements.

2.2. Gas path analysis

In this study, one of the most accurate types of gas analysis has been used. It is based on nonlinear model and taking into account the possibility of accuracy of measurements. For this purpose, a precise software model has first been developed that fully simulates the gas turbine behavior. In addition to the model, there should be functional gas turbine data. With actual performance data and simulator model, the gas path analysis algorithm, as presented in Figure 4 is as follows:

- the input and the initial values for the model parameters are given to the algorithm;
- the algorithm executes the model and the model output is generated;
- the model output is compared with the actual output data (corresponding to the same input); based on the difference value, these two parameter values are updated;
- the algorithm is repeated with the updated parameters from the first step;
- when the output of the model is identical to the updated parameters with the actual output, real parameters have been identified.

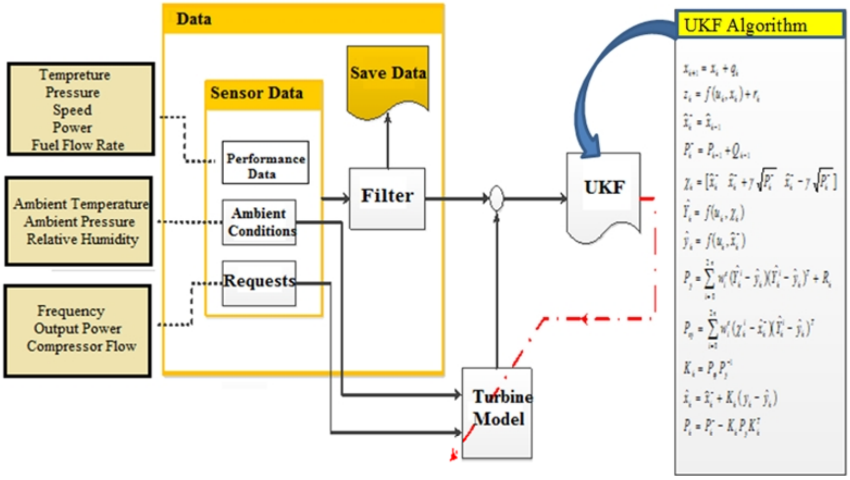


Fig. 4. gas path analysis algorithm.

It should be noted that the more the measurements are, the simpler and accurate the results will be calculated. But usually the number of parameters is greater than the number of measured outputs. Therefore, if a single operating point is used, the wrong values for the parameters may be calculated. For this reason, in the explained algorithm, enough input and output data must be considered for the operation of the steady state operating conditions of the turbine.

Given that the number of operating points used in the algorithm is too much, if one of the measurements is inaccurate, the algorithm does not converge correctly. In this case, two conditions may occur; either the algorithm does not converge or the output of the corresponding model will differ from the output of the system. Therefore, the faulty sensor can be detected. If the latter case happens, it means that the calculated data with a certain offset for the sensor is defective and the faulty value is also known. If the first case happens, it would be harder to detect the faulty sensor. In such case, all sensors should be checked to detect a faulty sensor. In this way, a sensor is assumed to be defective; the sensor data is removed from the calculation and the algorithm is executed. If the algorithm is correctly converged, then the removed sensor is defective and the predicted value by the algorithm for that sensor indicates the sensor's deviation. With this method, it's best to check for sensors that are more likely to fail.

3. Results

The general algorithm for fault detection in the GPA method with the use of a UKF estimation method will have some disadvantages if a single operating point is used (the classical method). The most important limitation in the application of GPA is the lack of measurements and therefore the system's uncertainty. The single-point method, without prior knowledge of the turbine condition, is not able to determine the fault intensity. Some of the single-point method disadvantages are mentioned by Stamatis et al.;2011 including the following:

only gives the answer when the fault location is known.

It is not enough when measurements are less than the parameters

One of the reasons for the development of other methods (including using multi operating points known as multi-point method) is the limitation in the number of measurements, which will be overcome by choosing multipoint method. The benefits of the multi-point method to the single point method in the UKF estimation have been illustrated in the following examples. At first, a single operating point with the characteristics listed in Table 1 is chosen to be used for the estimation algorithm.

The first and fourth health parameters in the model are given faulty data. Using the UKF fault estimation algorithm, the results are presented in Figure 5.

Table 1. The first operating point of the turbine.

Power (MW)	NPT (RPM)	P_0 (bar)	T_0 (C)
20	7700	1.013	-15

	Cm1	Cm2	Cm3	CE1	CE2	CE3	Tm1	Tm2	Tm3	Tm4	TE1	TE2	TE3	TE4
real	-3	0	0	-2	0	0	0	0	0	0	0	0	0	0
simulated	-1.95	-1.11	-0.17	-0.61	-0.46	-0.55	0.782	0.18	0.593	0.074	0.093	0.165	-0.2	-0.34

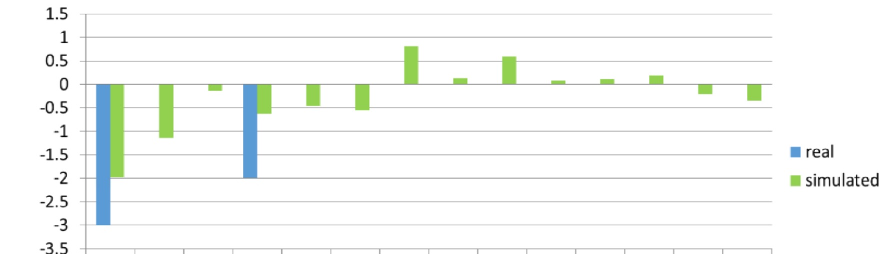
Fig. 5. Estimated faults for 14 health parameters using the first operating point.

The fault estimation for the given operating point for 14 model health parameters are shown with green bars. The blue bars are the faults that were given to the health parameters of the assumed affected model. At the bottom of the figure, the numbers written in the first row are the model health parameters faults and second line numbers are the fault of the health parameters that UKF estimated for the model. As can be seen, the UKF did not correctly detect the faults using a single operating point. In other words, not only faults are attributed to defective parameters, but also to the healthy symptoms which is also known as smearing effect. Also, the fault intensities are not correctly estimated.

The operation was repeated for the second operating point, the characteristics of which are shown in Table 2. For this point, only the power value has changed compared to the previous one. Corresponding results from the estimation algorithm are shown in Figure 6. As can be seen, the UKF has failed again to correctly identify the model faults.

Table 2. The second operating point of the turbine.

Power (MW)	NPT (RPM)	P_0 (bar)	T_0 (C)
22	**7700**	**1.013**	**15**



	Cm1	Cm2	Cm3	CE1	CE2	CE3	Tm1	Tm2	Tm3	Tm4	TE1	TE2	TE3	TE4
real	-3	0	0	-2	0	0	0	0	0	0	0	0	0	0
simulated	-1.97	-1.13	-0.13	-0.63	-0.45	-0.55	0.815	0.128	0.601	0.075	0.111	0.185	-0.2	-0.35

Fig. 6. Estimated faults for 14 health parameters using the second operating point.

Some other operating points given in Table 3 and Table 4. have also been utilized for the UKF algorithm, the results of which are compared with the actual values of the faulty model in Figures 7 and 8 respectively.

Table 3. The third operating point of the turbine.

Power (MW)	NPT (RPM)	P_0 (bar)	T_0 (C)
16	**7700**	**0.89**	**30**

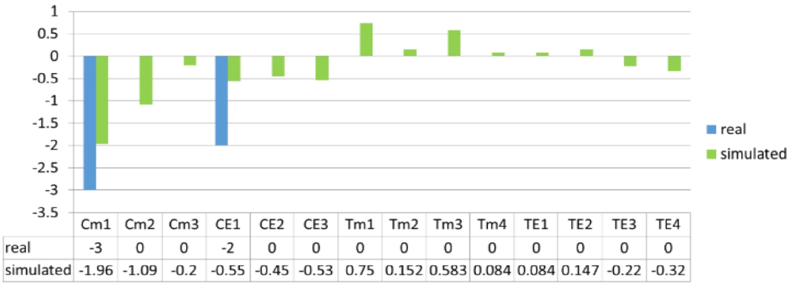


Fig. 7. Estimated faults for 14 health parameters using the third operating point.

Table 4. The fourth operating point of the turbine.

Power (MW)	NPT (RPM)	P_0 (bar)	T_0 (C)
17	7500	1.013	0

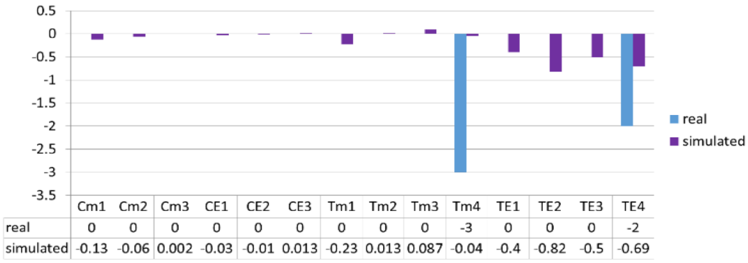


Fig. 8. Estimated faults for 14 health parameters using the fourth operating point.

In order to overcome the smearing problem, the multi-point method has been utilized. This means that several operating points have been applied in the UKF algorithm for health parameters estimation. In Figure 9, the attributed faults to the health parameters are presented with blue bars. The estimated faults by the UKF estimator for 14 health parameters are illustrated with orange bars. As can be seen, the usage of multi-point method shows a significant improvement over the single-point. The faulty parameters are correctly identified and their intensities are well estimated with acceptable approximation.

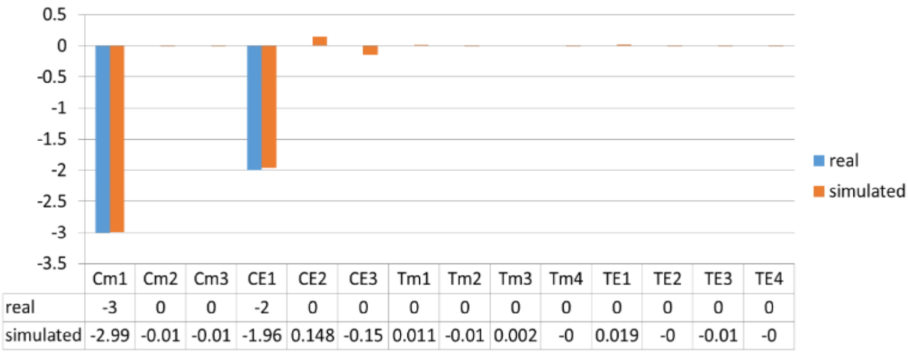
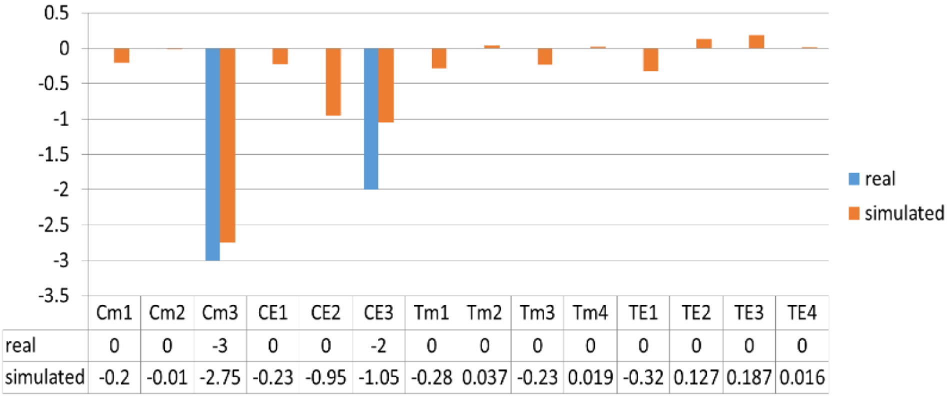


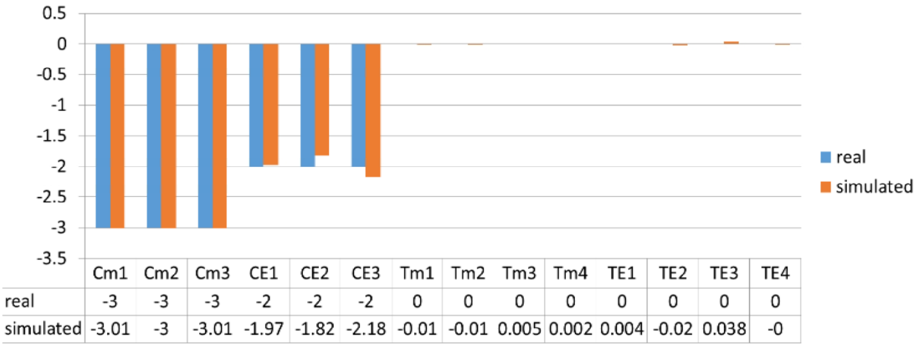
Fig. 9. Fault estimation for 14 health parameters using a multi-point method (first example).

In the following, the results are presented for several other examples, which are presented in Figures 10 to 12.



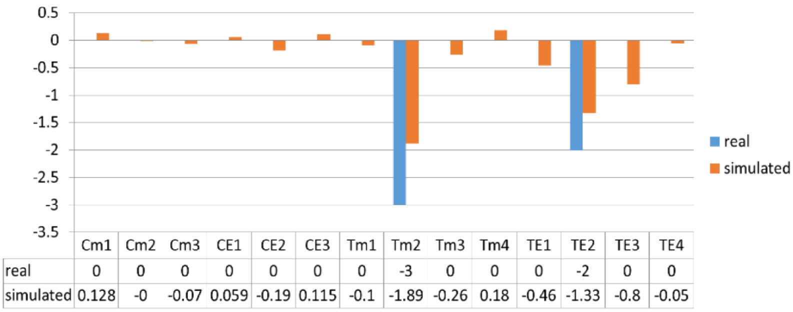
	Cm1	Cm2	Cm3	CE1	CE2	CE3	Tm1	Tm2	Tm3	Tm4	TE1	TE2	TE3	TE4
real	0	0	-3	0	0	-2	0	0	0	0	0	0	0	0
simulated	-0.2	-0.01	-2.75	-0.23	-0.95	-1.05	-0.28	0.037	-0.23	0.019	-0.32	0.127	0.187	0.016

Fig. 10. Fault estimation for 14 health parameters using a multi-point method (second example)



	Cm1	Cm2	Cm3	CE1	CE2	CE3	Tm1	Tm2	Tm3	Tm4	TE1	TE2	TE3	TE4
real	-3	-3	-3	-2	-2	-2	0	0	0	0	0	0	0	0
simulated	-3.01	-3	-3.01	-1.97	-1.82	-2.18	-0.01	-0.01	0.005	0.002	0.004	-0.02	0.038	-0

Fig. 11. Fault estimation for 14 health parameters using a multi-point method (third example).



	Cm1	Cm2	Cm3	CE1	CE2	CE3	Tm1	Tm2	Tm3	Tm4	TE1	TE2	TE3	TE4
real	0	0	0	0	0	0	0	-3	0	0	0	-2	0	0
simulated	0.128	-0	-0.07	0.059	-0.19	0.115	-0.1	-1.89	-0.26	0.18	-0.46	-1.33	-0.8	-0.05

Fig. 12. Fault estimation for 14 health parameters using a multi-point method (fourth example).

In all of these figures, orange bars are related to the estimated value of health parameters by the UKF. The blue bars are the given faults to the model health parameters. At the bottom of each figure, the numbers written in the first row are the model health parameters fault values and the second row numbers are the fault of the health parameters that UKF has estimated.

As can be seen from all above figures, the smearing effect continues to be present even for small quantities. For this reason, a certain number of health parameters are assumed to be fixed with zero deviation in the model for each run (use of bank of KFs). For example, a set of 16 KFs have been used for the engine model with 15 different sets of health parameters as illustrated in Table 5 and Table 6,**Błąd! Nie można odnaleźć źródła odwołania.** with faulty compressor (the first three health parameters are assumed to be deviated 2% from their healthy conditions). The estimation results from each parameter sets are demonstrated. By averaging the numbers in each health parameters, the final estimations are demonstrated at the last line. The average numbers are considered to be zero if less than a constant limit. The same procedure is repeated with other sets of health parameters for a model with a faulty gas generator (4th, 5th, 12th and 13th health parameters are assumed to be deviated 2% from their healthy conditions).

Table 5. The Health parameters estimation with the use of BKs for the engine model with faulty compressor.

	X1	X2	X3	X4	X5	X6	X7	X12	X13	X14	X15
Model with KF_1	-2.98	-2.98	-1.68	0	0	0	0	0	0	0	0
Model with KF_2	-2.98	-2.98	-1.68	0	0	0	0	0	0	0	0
Model with KF_3	-2.98	-2.98	-1.68	0	0	0	0	0	0	0	0
Model with KF_4	-2.98	-2.98	-1.68	0	0	0	0	0	0	0	0
Model with KF_5	-2.98	-2.98	-1.68	0	0	0	0	0	0	0	0
Model with KF_6	-2.87	-2.87	-1.68	0	0.497	0	0	0	0	0	0
Model with KF_7	-2.85	-2.85	-1.68	0	0.582	0	0	0	0	0	0
Model with KF_8	-2.85	-2.85	-1.68	0	0.594	0	0	0	0	0	0
Model with KF_9	-2.98	-2.98	-1.68	0	0	0	0	0	0	0	0
Model with KF_{10}	-2.74	-2.74	-1.68	0	0	0	0	0.542	0	0	-0.429
Model with KF_{11}	-2.41	-2.41	-1.67	0.791	0	0.82	0	0	0	0	0
Model with KF_{12}	-2.34	-2.34	-1.67	0.883	0	0.767	0	0	0	0	0
Model with KF_{13}	-2.98	-2.98	-1.68	0	0	0	0	0	0	0	0
Model with KF_{14}	-2.58	-2.58	-1.67	0.524	0	0	0	0	0.41	0	-0.744
Model with KF_{15}	-2.39	-2.39	-1.67	0.744	0	0.849	0	0	0	0	0
Model with KF_{16}	-2.29	-2.29	-1.67	0.888	0	0.692	0	0	0	0	-0.432
	-2.761	-2.761	-1.676	0	0	0	0	0	0	0	0

Table 6. The Health parameters estimation with the use of BKs for the engine model with faulty GG.

	X1	X2	X3	X4	X5	X6	X7	X12	X13	X14	X15
Model with KF_1	0.00	0.00	0.00	0	-4.729	0	0	0	-2.624	0	0
Model with KF_2	0.00	0.00	0.00	0	-4.735	0	-0.57	0	-2.511	0	0
Model with KF_3	0.00	0.00	0.00	0	-4.733	0	0	0	-2.346	-0.785	0
Model with KF_4	0.00	0.00	0.00	0	-4.726	-0.845	0	0	-1.867	0	-0.783
Model with KF_5	0.00	0.00	0.00	-1.668	0	0	0	-4.846	0	0	0
Model with KF_6	0.00	0.00	0.00	-1.681	0	0	-1.931	-3.9	0	0	0
Model with KF_7	0.00	0.00	0.00	-1.691	0	-0.94	0	-2.975	0	-2.158	0
Model with KF_8	0.00	0.00	0.00	-1.705	0	-1.518	-0.642	-1.564	0	-0.693	-1.405
Model with KF_9	0.00	0.00	0.00	-1.632	0	0	0	-0.858	-1.876	0	0
Model with KF_{10}	0.00	0.00	0.00	-1.633	0	0	-0.403	-0.827	-1.805	0	0
Model with KF_{11}	0.00	0.00	0.00	-1.629	0	0	0	-0.779	-1.699	-0.556	0
Model with KF_{12}	0.00	0.00	0.00	-1.617	0	-0.612	0	-0.64	-1.388	0	-0.566
Model with KF_{13}	0.00	0.00	0.00	-2.13	0	0	0	-6.4	0	0	0
Model with KF_{14}	0.00	0.00	0.00	-2.088	0	0	0	-1.146	-2.491	0	0
	0.00	0.00	0.00	-1.75	-2.10	0.00	0.00	-2.39	-2.07	0.00	0.00

4. Conclusion

GPA is one of the methods used for fault detection for gas turbine engines which can be based on a linear or nonlinear model. A general algorithm for detecting the gas path diagnosis is using an estimation method with a UKF algorithm based on a single operating point (the classical method) although it has some disadvantages such as the lack of measurements and consequently, the uncertainty of the system, as well as the estimated fault. Also, by using this method, the previous knowledge of the turbine condition is required to determine the intensity of the fault. To overcome these limitations, the multi-point method was used. Using this method, the health parameters were attributed to a faulty model and the UKF algorithm estimated the faults, based on multi operating conditions extracted from the IGT25 database. The results showed that attributed faults to health parameters were estimated with a much lower error than with the single-point method. Therefore, the multipoint application for UKF algorithm showed a significant improvement over the single-point mode in estimating the faults and the application of bank of KFs enhanced the smearing effect in both methods.

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