Proceedings of the ASME 2022
International Mechanical Engineering Congress and Exposition
IMECE2022
June 13-17, 2022, Rotterdam, The Netherlands

GT2022-82037

COMPARING DIFFERENT SCHEMES IN A COMBINED TECHNIQUE OF KALMAN FILTER, ARTIFICIAL NEURAL NETWORK AND FUZZY LOGIC FOR GAS TURBINES ONLINE DIAGNOSTICS

Simone Togni[1], Theoklis Nikolaidis[1], Suresh Sampath[1]

[1]Cranfield University, Cranfield, United Kingdom

ABSTRACT

The paper presents research on the online performance-based diagnostics by implementing a novel methodology, which is based on the combination of Kalman Filter, Artificial Neural Network, Neuro-Fuzzy Logic and Fuzzy Logic. These methods are proposed to improve the success rate, increase the flexibility, and allow the detection of single and multiple failures. The methodology is applied to a 2-shaft industrial gas turbine engine for the automated early detection of single and multiple failures with the presence of measurement noise.

The methodology offers performance prediction and the possibility of utilizing multiple schemes for the online diagnostics. The architecture leads to three possible schemes. The first scheme includes the base methodology and enables Kalman Filter for data filtering, Artificial Neural Network for the component efficiency prediction, the Neuro-Fuzzy logic for the failure quantification and the Fuzzy Logic for the failure classification. For this scheme, a performance simulation tool (Turbomatch) is used to calculate the thermodynamic baseline. The second scheme replaces Turbomatch with the Artificial Neural Network, that is used to calculate the deteriorated efficiencies and the reference efficiencies. The third scheme is identical to the first one but excludes the shaft power measurements, which are not available in aero engines or might not be usable for some power plant configurations.

The paper compares the performance of the three methodologies, with the presence of measurement noise (0.4% reference noise and 2.0% reference noise), and 24 types of random single and multiple failures, with variable magnitude. The first methodology has been already presented by Togni et al. [10], whereas the other two methodologies and results are part of the PhD thesis presented by Togni [18] and they extend the applicability of the method. The success rate, targeting the correct detection of the of the failure magnitude ranges between 92% and 100% without measurement noise and ranges between 66% and 83% with measurement noise. Instead, the success rate of the classification, targeting the correct detection of the type of failure ranges between 93% and 100% without measurement noise and between 85% and 100% with measurement noise.

Keywords: Gas Turbine; Performance-Based Diagnostics; Artificial Neural Network; Fuzzy logic; Kalman filter; Data Analytics; Data Filtering; Diagnostics; Multiple Failures; Gas Turbine; Health Monitoring; Failure Classification; Gas Turbine Diagnostics, Machine Learning; Artificial Intelligence.

NOMENCLATURE

ANN	Artificial Neural Network
BBN	Bayesian Belief Network
ES	Expert Systems
FL	Fuzzy Logic
GA	Genetic Algorithms
GT	Gas Turbine
HP	High Pressure
KF	Kalman Filter
LGPA	Linear Gas Path Analysis
LP	Low Pressure
NFL	Neuro Fuzzy Logic
NLGPA	Non Linear Gas Path Analysis

1. INTRODUCTION

The performance-based gas path analysis is a topic that has been studied in the last 40 years since Urban [1] defined the possibility of making diagnostics on the gas turbines components, based on the performance parameters. Before Urban used the performance to make its predictions on gas turbine failures, the consolidated technique that has been used is the vibration analysis. The vibration analysis is still the most widely used technique to make diagnostics and prognostics and is capable, among others, of detecting unbalances, rotor cracks, rotor bow, etc. Another technique that is applied, is the lube oil analysis that consists of analyzing the oil for debris, caused by mechanical friction that can indicate malfunction of the gas turbine.

- Despite the fact that the vibration analysis and the lube oil analysis offer a reliable detection of the malfunctions, the performance-based diagnostics has two critical advantages.
- detecting the performance loss of each component.
- the possibility of detecting malfunctions early on time, before the vibration probes can produce a consistent vibration, or the lube oil can collect some debris.

The importance of health monitoring in the gas turbine industrial system and in the aero engines has grown in the last two decades. One of the motivations behind this growth is the economic advantage. As reported by Verbist et al. [2] in the recent years, the technical enhancements of the gas turbines technology decreased fuel consumption. However, due to the fuel price increase over the same period, the fuel cost still counts for one-third of the operating expenses. The authors clarify that to reduce the operating costs, the engines are demanded to operate longer and reduce maintenance costs. For instance, the costs of maintenance for gas fired combined cycle plants can reach 50% of the total O&M costs [3] and represent 7% of the overall project cash flow. Additionally, statistic studies conducted over 3000 E and F class engines concluded that the unplanned maintenance cost can reach 8% of the O&M costs, or 2% of net revenue income and the loss of revenue can reach the 15% of the O&M cost or 5% of net revenue income [4].

Any proposed methodology should offer an easy way to detect the components failure or their deterioration [5]. The main features that a methodology must contain [6] are:

- be able to work with an increasing amount of data available and new sensors
- be able to model and detect instances both at part load and baseload
- have an easy to use and clear user interface
- be flexible enough to include automated information, but also user experience

Additionally, the methodology should be able to detect the failure of single components in a multi component engine and should be able to detect any other combination of multiple failures. Moreover, a robust methodology should also consider the measurement noise, as they are part of the any working engine. Instead, the presence of redundant measurements can exclude the bias in the measurements [7].

In the last decade the problem was approached by utilizing single methodologies. The most widely used are the LGPA, NLGPA, KF, ANN, GA, FL, BBN and ES. The reason for single methodologies was mostly related to the limitation of computational power. However, as summarized by Fentaye et. al [15], the single methodologies have limitations, that do not allow to address all the problems. Given the increase of computational power, the combination of methodologies became a feasible solution.

Among the literature published in the last years, Verma et al. [8], proposed a genetic fuzzy logic with a radial basis function neural network. The aim of the genetic fuzzy is to automatically tune the failures based on genetic algorithm analysis while the neural network is used to isolate the noise. The methodology is tested for a single deterioration case scenario. Kumar et al. [9], instead coupled the fuzzy logic with the support vector machine not only for the diagnostics but also for the remaining lifetime estimation.

Finally, Togni et. al [10] coupled the Kalman filter, the artificial neural network, and the fuzzy logic to detect single and multiple failures, also with the presence of measurement noise. In this methodology, a reference physical model has been used to calculate the differences of the deteriorated model from the new model. Moreover, among the measurements, the power has been used. This makes the methodology suitable only for the detection of power plant gas turbine, with the generator directly connected to the gas turbine. Moreover, the presence of the physical model limits the applicability in case the model is not available.

The aim of the current paper is to compare what obtained by Togni [10] with a scheme without physical model, where the ANN is used both as predictor and as reference and with a scheme that excludes the power measurement. These structures will lead to two additional schemes: scheme 2, where the thermodynamic model is replaced by the ANN; scheme 3, where the thermodynamic model is used, but the power measurement is excluded. These schemes and results are already part of the work presented by Togni in his PhD thesis [18].

Scheme 2 expands the applicability of the methodology to data driven only solutions, or to situations where the thermodynamic model is not suitable for online detection.

Scheme 3, instead, expands the applicability of the methodology to aero engines where the power measurement is not an option, and to layout that connects multiple components to a power generator.

2. METHODOLOGY

The proposed method compares the application of the methodology shown by Togni et al. [10] and composed by the Kalman Filter for the noise reduction, the Artificial Neural Network for the efficiency prediction, the Neuro Fuzzy Logic for the severity quantification and the Fuzzy Logic for the failure classification. (**Figure *1***), with two additional variants, as presented by Togni [18] in his PhD thesis.

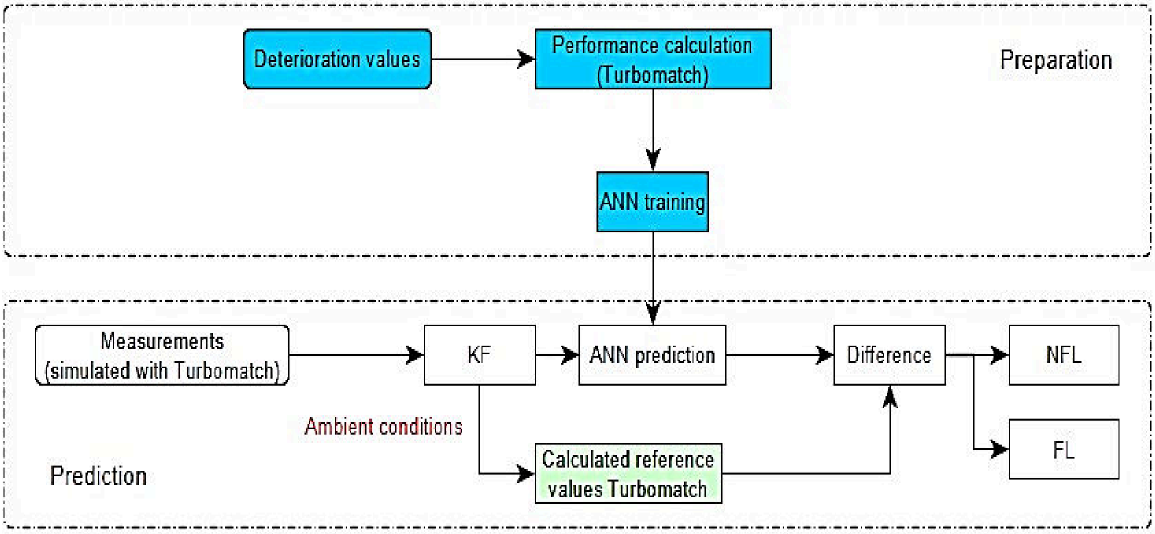

Figure 1: Structure of the methodology. Source [18]

The methodology is divided in three macro areas:

a. The KF for the data filtering.
b. The ANN for the efficiency prediction.
c. The NFL and FL for the failure quantification and classification.

The KF is the first module that the data sees, and it is meant to isolate the noise from the data. The KF is not meant to work with biased signals.

The ANN is a feedforward neural network with 3 hidden layers. The ANN is trained with values created from a gas turbine performance model created in Turbomatch. Turbomatch is a software-based Gas Turbine performance simulation tool developed by the Propulsion Engineering Centre (formerly department of Power and Propulsion), at Cranfield University [11]. The simulation data are a favorite choice as compared to the field data. As reported by Simon et. al [12], in fact, the reliability reached by the engines as per today makes unlikely for a gas turbine to experience multiple failures. Therefore, it is challenging to have a sufficient palette of real data including distinguished failures for testing. Given this, a simulation of gas turbine malfunctions has been considered.

The NFL rank the failures on a scale moving from a good status to an alarm level for one or multiple components of the gas turbine. The FL is also integrated in the same section and is used for the failure classification. The categorization is done through two boxes: one for the compressor fouling, turbine fouling; another for the turbine erosion. These two boxes are proposed for each component in the gas turbine **Figure *2***.

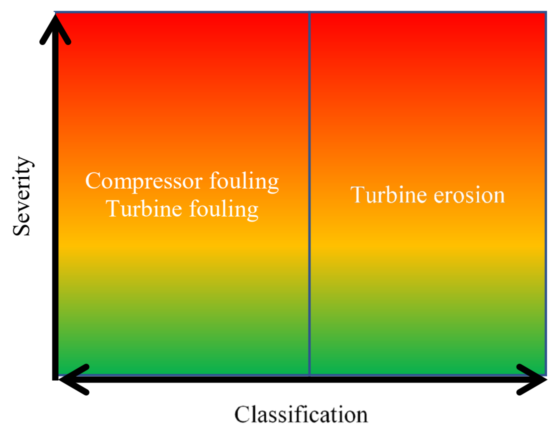

Figure 2: Chart for the quantification/classification of the results

The combination of the three blocks combines the strength of each module, and the flexibility they offer lead to three possible schemes:

a. Scheme 1: the first scheme is composed by the Kalman filter placed at the beginning to filter for noise; after it comes the ANN used to predict the performance parameters; the values from Turbomatch are used as reference to calculate the difference that will be used by the fuzzy logic to make the quantification first and the classification after. This scheme (**Figure 3**) is considered as the baseline for this methodology [10], whereas the others are considered variants [18].

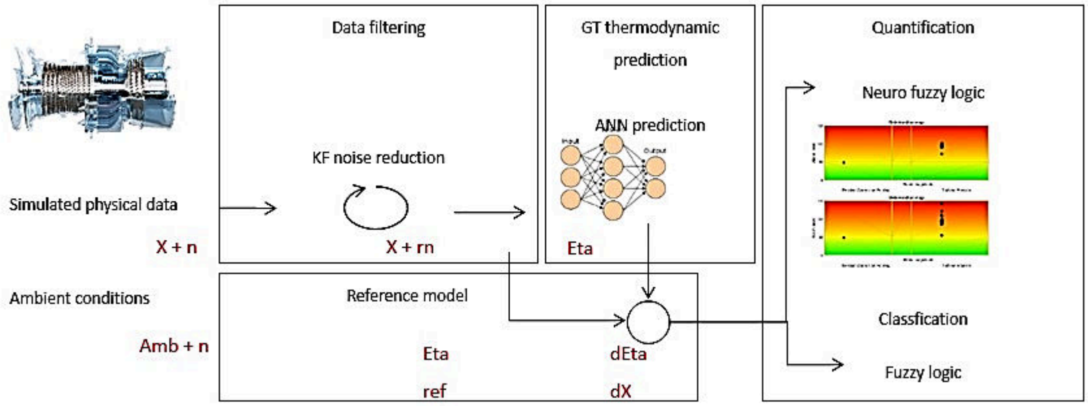

Figure 3: Flow chart representing the concept behind the diagnostics tool – Turbomatch used as reference (Scheme 1 - Scheme 3) – Where X are the measurements, n is the noise, rn is the remaining noise, dEta and dX are the delta efficiency and measurement, Amb are the ambient conditions and ref is the reference of the non-deteriorated engine. Source of the picture [10]

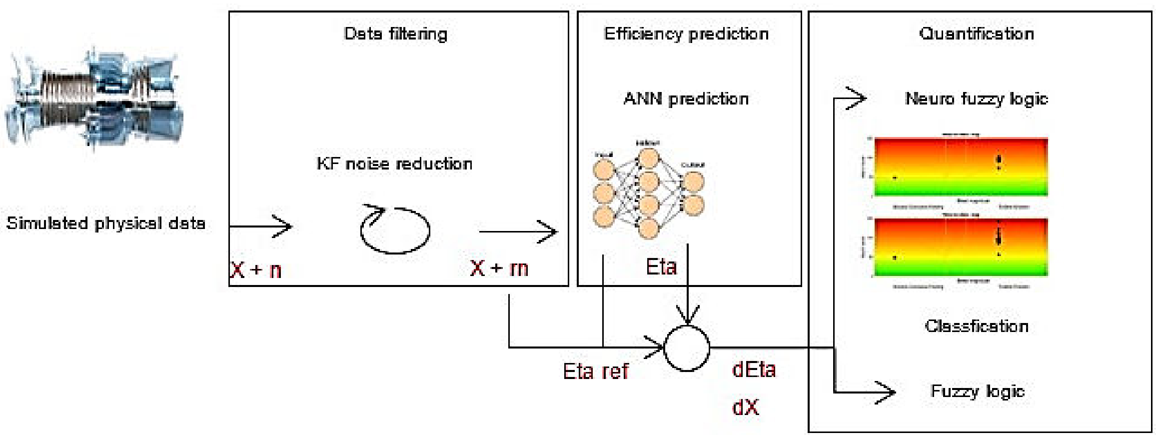

Figure 4: Flow chart representing the concept behind the diagnostics tool – ANN used as reference (Scheme 2) – Where X are the measurements, n is the noise, rn is the remaining noise, dEta and dX are the delta efficiency and measurement, Amb are the ambient conditions and ref is the reference of the non-deteriorated engine. Source of the picture [18]

b. Scheme 2: the second scheme uses the Kalman filter at the beginning as per scheme 1; after it also comes the ANN that is used to predict the performance values of the deteriorated engine and to predict the performance reference of the new engine as well; the difference is then calculated among the two ANN values and passed to the fuzzy logic for the quantification and classification phase (**Figure *4***). This scheme has the advantage of being faster, since Turbomatch must not be called from the routine, and is not requiring the ambient signals.
c. Scheme 3: the third scheme starts also from the Kalman filter that is used upfront; the second part, the ANN is built without the power measurement. The scheme as such does not change, but the block is different. The prediction of the deteriorated engine performance is done with the ANN while the reference is from Turbomatch as per scheme 1 (**Figure 3**). This scheme can be used in case the power measurement is not available, or the power measurement is not referring only to the gas turbine.

2.1 Gas turbine performance modelling

The gas turbine considered is a 2-spool industrial gas turbine of small size providing 11.9 MWe power output with a pressure ratio of 17. The gas turbine has two compressors, one LP and one HP, two turbines, one HP and one LP one burner and one extraction for the cooling system. The efficiency values of the compressor and of the turbine are taken from [13] that proposes values of an engine with a pressure ratio of 17. The overall values are taken from the freely published values of an engine of that size. In particular, the pressure ratio is 17, the power is 11.9

MWe, the exhaust temperature is 485°C and the inlet mass flow is 41.6 kg/s. The cooling is modelled with one extraction after the HP compressor. The amount of cooling air at each pressure level has been tuned to match the exhaust gas temperature. The performance values are modelled in Turbomatch the thermodynamic cycle modeler built and maintained in Cranfield [11].

2.2 Deterioration profile simulation

The types of deterioration considered are the compressor fouling, the turbine fouling and the turbine erosion and this is applicable for a total of four components. The combinations of the types of failures and the number of components lead to a certain number of combinations and among those 24 have been selected for this simulation (**Table *1***). The combinations include no failure, meaning that the engine performs as per design, failure of single components and failure of multiple components.

	LP comp fouling	HP comp fouling	HP turbine fouling	HP turbine erosion	LP turbine fouling	LP turbine erosion
Case-0						
Case-1	X					
Case-2		X				
Case-3			X			
Case-4				X		
Case-5					X	
Case-6						X
Case-7	X	X				
Case-8	X		X			
Case-9	X			X		
Case-10	X				X	
Case-11	X					X
Case-12		X	X			
Case-13		X		X		
Case-14		X			X	
Case-15		X				X
Case-16			X			X
Case-17				X	X	
Case-18	X	X		X		
Case-19	X	X			X	
Case-20	X	X				X
Case 21	X	X	X		X	
Case 22	X	X	X			X
Case 23	X	X	X		X	
Case 24	X	X	X			X

Table 1: Deterioration combination: the deterioration is simulated in all the components considering the ratio reported in the literature to make the simulation realistic [14].

The ratio between efficiency and flow capacity is set to 1:2. This is well summarized by Fentaye et. al [15] who reports a ratio between 1:2 and 1:3. The range of deterioration that is considered is between 0.0% and 7.7% to give room to the ANN to cover all possible conditions. The deterioration levels that are reported from the literature in fact rarely go beyond 5.0%.

2.3 Measurement selection and uncertainty

The typical measurement equipment for an industrial gas turbine has been described by Jiang et al. [16] and they are reflected in the 2-spool engine presented here **Table *2***. The measurement noise is equal to the one already presented by Togni et. al [10] and is derived by the reference noise presented by Joly et. al [17] and referring to an aviation gas turbine.

		Reference noise	Included in ANN
LP compressor inlet pressure	p_1	0.1%	No
LP compressor inlet temperature	T_1	0.4%	No
LP compressor inlet relative humidity	RH_1	0.4%	No
LP compressor exhaust pressure	p_2	0.1%	Yes
LP compressor exhaust temperature	T_2	0.4%	Yes
HP compressor exhaust pressure	p_3	0.1%	Yes
HP compressor exhaust temperature	T_3	0.4%	Yes
Mass flow rate	mf	0.4%	No
HP turbine exhaust pressure	p_5	0.1%	Yes
HP turbine exhaust temperature	T_5	0.4%	Yes
LP turbine exhaust pressure	p_6	0.1%	No
LP turbine exhaust temperature	T_6	0.4%	Yes
Power	P	0.4%	Yes*

Table 2: Noise level for reference noise level 0.4% and measurements included in the ANN network. *Not included in scheme 3

The measurement location is specified in **Figure *5***. The magnitude of the measurement faults is 0.4% reference and 2.0% reference. At each noise level, the ratio between pressure noise and temperature noise remains unchanged. For instance, with 0.4% reference measurement noise, p_1 has 0.1% noise and T_1 0.4%. With 2.0% reference measurement noise, the values are 5 times higher. The aim is to verify how the methodology can react and how robust is, with the presence of high measurement noise.

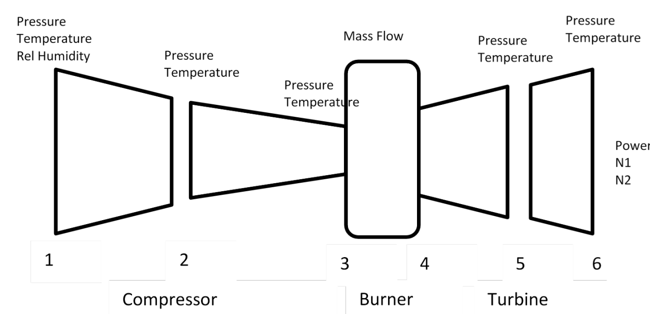

Figure 5: Gas turbine measurements location

3 RESULTS AND DISCUSSION

To verify the robustness of the methodology, the scenario that has been considered is the random deterioration. Here 203 points with degradation within 0.15% - 7.4%; single, multiple and no failures from **Table *1*** are picked. In this case, the measurement noise is also included. The noise levels included are the nominal - 0.4% - and the maximum - 2.0%. The results present in this article have been presented by Togni in his PhD thesis [18] and they are compared to the scheme 1 already presented by Togni [10].

The output of the tests is the success rate. For the quantification, the simulated point is counted if it lies within 3σ standard deviation and for the classification is counted if classified in the right category (also if the quantification is outside the 3σ standard deviation). The standard deviation 1σ is calculated from a dry run with nominal noise (0.4%) and constant deterioration of multiple components. The calculated value is ±2.06 for 1σ and therefore, ±6.18 for 3σ.

For the classification, instead, the success rate considers if a point falls in the appropriate category. It must be reminded that the failures are simulated, therefore it is known what type of failure is injected and should be detected afterwards.

Comparing the three schemes with the random deterioration and with nominal noise the quantification success rate is above 92% with all the schemes (**Table 3**). Considering the random nature of the selected points, there can be a variability between the schemes. However, it seems scheme 2 performs slightly better than the others. It is showen that scheme 1 has a success rate of 92% on the HP compressor, which is remarkable, but it is lower than the 97.5% obtained with the scheme 2.

Quantification - Random deterioration 0.4% noise - KF			
	Scheme 1	Scheme 2	Scheme 3
LP comp	97.0%	100%	99.0%
HP comp	92.0%	98.5%	97.0%
HP turb	98.5%	97.5%	99.0%
LP turb	99.0%	97.5%	95.5%

Table 3: Quantification success rate with random deterioration and 0.4% measurement noise and KF

Considering the classification, the results varied among the schemes. This is attributed to the nature of the test case, which does not allow to compare the three schemes directly. Another reason is the different characteristics of the schemes. With regards to the classification rate, it can fall to 93.2% with scheme 2. This depends on the additional uncertainty created by the reference that moved from Turbomatch to the ANN. However, with the scheme 1 the classification rate is above 95.1%. The absence of the power signal in the ANN in scheme 3, does not have a decisive effect in the classification as the success rate remains above 95.0% as compared to 95.1% in scheme 1 (**Table 4**).

Classification - Random deterioration 0.4% noise – KF			
	Scheme 1	Scheme 2	Scheme 3
LP comp fouling	98.3%	93.7%	96.8%
HP comp fouling	97.9%	98.2%	96.2%
HP turb fouling	100%	100%	100%
HP turb erosion	95.1%	98.2%	95.0%
LP turb fouling	100%	100%	100%
LP turb erosion	96.9%	93.2%	96.2%

Table 4: Classification success rate with random deterioration and 0.4% measurement noise and KF

The results with 2.0% reference noise and constant deterioration contradicts what has been seen with 0.4% reference noise. With higher noise in fact, the scheme showing best results is scheme 3, where the success rate is above 72.1% **Table 5**. With scheme 1, the additional power measurement disturbance, introduce additional uncertainties as compared to scheme 3 and the success rate is above 70.1%. Scheme 2 instead, includes the uncertainty of the reference predicted by the ANN, and is also disturbed by the measurement noise, and the uncertainty of all the measurement as scheme 1. The success rate is above 65.7% and it is the only scheme with success rate below 70%.

Quantification - Random deterioration 2.0% noise - KF			
	Scheme 1	Scheme 2	Scheme 3
LP comp	76.1%	76.1%	82.1%
HP comp	73.6%	70.1%	74.1%
HP turb	70.1%	65.7%	72.1%
LP turb	83.1%	78.6%	80.1%

Table 5: Quantification success rate with random deterioration and 2.0% measurement noise and KF

The classification success rate is affected less by the measurement noise. The single point must fall into the right category (fouling vs erosion) as compared to the quantification, where the point has to fall within 3σ. With 2.0% reference measurement noise, the best results are achieved with scheme 2, where the success rate is above 91.7% and generally above the success rate of scheme 1 and scheme 3 (**Table 6**). This means that the ANN has a better prediction in terms of reference for the failure classification. With scheme 1, the success rate is above 88.9% and with scheme 3, the results are above 84.7%. This means that the power measurement is beneficial for the failure classification.

Classification - Random deterioration 2.0% noise – KF			
	Scheme 1	Scheme 2	Scheme 3
LP comp fouling	97.7%	98.6%	95.2%
HP comp fouling	100%	98.5%	95.9%
HP turb fouling	96.0%	100%	100%
HP turb erosion	90.7%	91.7%	94.4%
LP turb fouling	100%	100%	100%
LP turb erosion	88.9%	93.9%	84.7%

Table 6: Classification success rate with random deterioration and 2.0% measurement noise and KF

It is shown that the results with 2.0% reference noise and KF show a success rate up to 20% lower than the results with 0.4% reference noise. However, KF method plays an important role in the overall architecture. This is evident as the quantification success rate without KF, falls to 51.7% with scheme 3 (**Table 7**). This means that the KF can recover up to 20% quantification success rate.

Quantification - Random deterioration 2.0% noise – no KF			
	Scheme 1	Scheme 2	Scheme 3
LP comp	56.7%	58.7%	60.2%
HP comp	56.2%	62.7%	53.2%
HP turb	59.2%	56.7%	51.7%
LP turb	74.1%	72.6%	64.7%

Table 7: Quantification success rate with random deterioration and 2.0% measurement noise

Similarly, to what observed with the 2.0% reference noise and KF, the classification is affected less by the measurement noise. Even without the KF in fact, the minimum classification success rate is 76.5% on LP turbine erosion and scheme 3 (**Table *8***). However, most of the results remain above 87% with scheme 2 outperforming the other schemes and a success rate above 94.4%. Interestingly, this result is even better than what obtained with the KF.

Classification - Random deterioration 2.0% noise – no KF			
	Scheme 1	Scheme 2	Scheme 3
LP comp fouling	99.1%	94.4%	99.0%
HP comp fouling	100.0%	97.8%	97.8%
HP turb fouling	100.0%	100%	100%
HP turb erosion	86.5%	94.7%	87.0%
LP turb fouling	100.0%	100%	97.7%
LP turb erosion	88.3%	96.0%	76.5%

Table 8: Classification success rate with random deterioration and 2.0% measurement noise

Another important aspect, which was evaluated among the schemes was the run time. The values that are compared are per sample and divided per each block in the schemes: the KF section used to pre-process the data, the ANN used to predict the performance values of the GT, the calculation section done through Turbomatch used to determine the reference values and the FL block that includes the NFL for the component health estimation and the FL for the failure classification. The total time varies depending on the type of the scheme used and on the configuration of the KF. Scheme 2, for instance, does not need Turbomatch calculation and can process one sample in less than half a second (**Table *9***). The reference scheme 1, requires 1.7s per point. Scheme 2, which excludes the Turbomatch prediction, reduces the process time per point to 0.4s. Scheme 3 instead, has a slightly quicker KF. Turbomatch processing is also faster, but that might be related to the computational performance, as the process remains the same.

The execution time of the schemes – Time per sample			
	Scheme 1	Scheme 2	Scheme 3
	[s]	[s]	[s]
KF	4.4E-01	3.4E-01	3.5E-01
ANN	1.7E-03	2.1E-03	1.0E-03
Turbomatch	1.2E+00	-	1.0E+00
FL	5.7E-02	5.9E-02	5.3E-02
Total	1.7E+00	4.0E-01	1.4E+00

Table 9: Execution time of the schemes

4 CONCLUSION

The comparison of the three schemes, shows that the methodology is adaptable to different GT layout and conditions. Moreover, the presented method is also able to perform even in the absence of a reference thermodynamic model (scheme 2). The time per sample makes all the schemes suitable for online diagnostics. Among the key findings:

- The combination of multiple techniques like the KF, ANN, NFL and FL make the methodology flexible, performant, and adaptable to multiple problems.
- The results vary among the schemes, but they remain solid and comparable, confirming the applicability of the methodology with all the three variants.
- The methodology can also be applied without a reference thermodynamic model, provided there are data to train the ANN beforehand.
- The processing speed makes the methodology suitable for online diagnostics with all the schemes. However, scheme 2 allow an additional processing time reduction as it is excluding the reference calculation.

ACKNOWLEDGEMENTS

This paper is not supported by any sponsorship and relies on open literature information and on Cranfield in house tools for performance modelling.

REFERENCES

[1]. Urban, L.A. (1973) Gas Path Analysis Applied to Turbine Engine Condition Monitoring. *Journal of Aircraft*; 10(7), pp.400–406.

[2]. Verbist, M. L., Visser, W. P. J., Van Buijtenen, J. P., & Duivis, R. (2011). Gas path analysis on KLM in-flight engine data. Proceedings of the ASME Turbo Expo. https://doi.org/10.1115/GT2011-45625

[3]. Grace, D. (2008) Combined-Cycle Power Plant Maintenance Costs; 10.1115/GT2008-51357.

[4]. Grace, D, & Christiansen, T. (2012) Risk-based assessment of unplanned outage events and costs for combined-cycle-plants. In Proceedings of the ASME Turbo Expo; https://doi.org/10.1115/GT2012-68435

[5]. Volponi, A. J. (2014) Gas turbine engine health management: Past, present, and future trends. Journal of Engineering for Gas Turbines and Power; https://doi.org/10.1115/1.4026126

[6]. D. Simon. (2012) Challenges in aircraft engine gas path health management. In Proceedings of the Tutorial on Aircraft Engine Control and Gas Path Health Management, Cleveland, OH, USA, 2012

[7]. L. J. Kerr, T. S. Nemec, G. W. Gallops. (1991) Real-Time Estimation of Gas Turbine Engine Damage Using a Control Based Kalman Filter Algorithm. The American Society Of Mechanical Engineers

[8]. Verma, R., Roy, N., & Ganguli, R. (2006) Gas turbine diagnostics using a soft computing approach. In Applied Mathematics and Computation; Available from: https://doi.org/10.1016/j.amc.2005.02.057

[9]. Kumar, A., Shankar, R., & Thakur, L. S. (2018) A big data driven sustainable manufacturing framework for condition-based maintenance prediction. Journal of Computational Science. Available from: https://doi.org/10.1016/j.jocs.2017.06.006

[10]. Togni, Simone, Nikolaidis, Theoklis, Sampath, Suresh. (2020). A combined technique of Kalman filter, artificial neural network and fuzzy logic for gas turbines and signal fault isolation.

Chinese Journal of Aeronautics. 34. 10.1016/j.cja.2020.04.015.
[11]. J. Palmer and T. Nikolaidis. (2015) "The TURBOMATCH Scheme for Gas Turbine Performance Calculations (ver. 2.0) - User Manual,".
[12]. Simon, D. L., Bird, J., Davison, C., Volponi, A., & Iverson, R. E. (2008). Benchmarking gas path diagnostic methods: A public approach. Proceedings of the ASME Turbo Expo. https://doi.org/10.1115/GT2008-51360
[13]. Pathirathna, K. A. B. (2013). Gas Turbine Thermodynamic and Performance Analysis Methods Using Available Catalog Data (Dissertation). Retrieved from http://urn.kb.se/resolve?urn=urn:nbn:se:hig:diva-17474
[14]. Mohammadi, E., & Montazeri-Gh, M. (2014). Simulation of full and part-load performance deterioration of industrial two-shaft gas Turbine. Journal of Engineering for Gas Turbines and Power. https://doi.org/10.1115/1.4027187
[15]. Fentaye, Amare & Baheta, Aklilu & Gilani, Syed & Kyprianidis, Konstantinos. (2019). A Review on Gas Turbine Gas-Path Diagnostics: State-of-the-Art Methods, Challenges and Opportunities. Aerospace. 6. 83. 10.3390/aerospace6070083.
[16]. Jiang, X., & Foster, C. (2014). Plant performance monitoring and diagnostics - Remote, real-time and automation. Proceedings of the ASME Turbo Expo. https://doi.org/10.1115/GT2014-27314
[17]. Joly, R. B., Ogaji, S. O. T., Singh, R., & Probert, S. D. (2004). Gas-turbine diagnostics using artificial neural-networks for a high bypass ratio military turbofan engine. Applied Energy. https://doi.org/10.1016/j.apenergy.2003.10.002
[18]. S. Togni (2020). An integrated combined methodology for the online gas turbines performance-based diagnostics and signal failure isolation. Ph.D. Thesis Cranfield University