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A diagnostics tool for aero-engines health monitoring using machine learning technique

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Abstract

In this work an integrated heath monitoring platform is proposed and developed for performance analysis and degradation diagnostics of gas turbine engines. The aim is to link engine measurable data to its health status.
A numerical tool has been implemented in order to calculate engine performance in design condition and to create a database of expected vales. Then different degradation levels have been introduced in the two main components, compressor and turbine of a single spool turbojet and the diagnostics instruments have been trained to detect the component fault.
In order to evaluate the performance prediction two different machine learning based techniques, namely, artificial neural network (ANN) and support vector machine (SVM) have been compared.
Synthetic data generation has been carried out to show how the degradation effects can affect the engine performance. The two main degradation causes considered are the compressor fouling and turbine erosion.
The machine learning techniques were applied with two aims: aero-engine performance prediction and health diagnostics. The study was carried out based on three samples flights, whose data were used for the training and testing process of the prediction and diagnostics tools.
The knowledge and the continuous monitoring of the engine health status can be crucial for maintenance and fleet management operations.

Keywords: Health Monitoring, Neural Network, diagnostics analysis.

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1. Introduction

Several factors could degrade propulsion and flight performance of aero-engines. The most common degradation mechanisms are associated to variations in blade surfaces due to erosion, fouling, debris deposit and the effect on the blade aerodynamics.

Fouling is the most common reason of compressor deterioration and is recognized as the source of about 70–85% of performance degradation in gas turbine engines. It occurs in the first 5-6 stages decreasing from the front to the back end of the compressor [1]. Fouling deterioration of gas turbine depends on two factors [2]: the exposure of the engine to compressor fouling based on its design parameters and the sensitivity of the gas turbine to a certain degree of imposed fouling. Source for fouling phenomena are dust, dirt, sand, ash and carbon particles and soft particles such as oil, unburned hydrocarbons, soot, etc. [3]. Fouling belongs to the group of recoverable deterioration and can be reduced or even eliminated by cleaning to restore the gas turbine engine flow path surfaces to near initial conditions.

Another cause of degradation is erosion phenomenon on turbine stages due to hard abrasive particles suspended in the air or gas stream. Erosion causes performance losses due to the decrease in surface roughness, an increase in blade tip clearance, blunting of the blade leading edge, thinning of the trailing edge and shortening of the blade chord [4-6]. In the turbine section, damage due to erosive particles that enter with the fuel is particularly severe.

The identification and prediction of the degradation phenomena mentioned above by detection of engine status is the challenge of recent research studies [7-8]. Diagnostics method consists in the implementation of an efficient health monitoring which investigates engine performance degradation observing component parameters compared to the same parameters of an “healthy” engine.

The key approaches useful for these kinds of problems are based on the use of gas path analysis (GPA), which aims to delivering early warning information about ongoing degradations through measurable changes in engine performance parameters. An interesting analysis of the measurements validation before they are used in GPA tools has been carried out in [9]. Several parameters should be taken into account in the implementation of prediction methods, these can be collected information from in-flight measurements or from engine model to estimate health indicators, which cannot be directly measured. In [10] the habitual problem related to the lack of data from real data acquisition system is overcome using multiple operating point minimization technique. Sallee et al. [11] have described how the two main engine-parameters, namely flow capacity and efficiency, are affected by the engine configuration and deterioration.

Regarding the machine learning techniques, neural networks (ANN) are most widespread because provides a viable tool for dealing with nonlinear problems and modelling complex and nonlinear dynamic systems with great flexibility and capability [12-17]. Barad et al. [18] proved that ANN-based performance healthy-monitoring tool is sufficiently robust and delivers an early warning compared with the mechanical parameters. Neural network can be trained to perform a particular function by adjusting the values of the connections between elements leading to a specific target output. Several kinds of ANN are used in the application jet engine fault diagnosis: dynamic neural networks [12], feed-forward neural network [19], Radial Basis Network (RBN) [20].

However, even if ANN can be only applied to the specified aero-engine type, often ANNs do not accurately describe the complex system to monitor aero-engine condition. While traditional artificial neural networks are constructed around the empirical risk minimization principle, which limits their generalization capability, support vector machines (SVM) indicates its superior ability in solving nonlinear regression problems. The SVM model has a similar functional form to ANN but has a better generalization performance, and a good ability to model complex problems in presence of data sets with several variables and with a limited set of available data for training.

Furthermore despite the good prediction performances of ANNs, they present disadvantages such as the tendency to over-fit, and although the training data may be very well fitted, the resulting function hasn’t got a general value. Moreover, the ANN needs large computational resources for training. Recently the SVM algorithm was successfully used as a novel powerful learning tool machine used for forecasting in several fields [21-22].

Therefore, in this paper we developed a data driven method which employs both artificial neural networks and support vector machines to build aero-engine monitoring model using a set of training data and testing data. The numerical results used for the models test show that the approach can provide an effective monitoring in aero-engine performance and it could identify the component (compressor or turbine) that presents degradation.

Nomenclature

Alt	Altitude [m]
f	training algorithm function
GPA	Gas Path Analysis
m	Flow rate [kg/s]
Mach	Mach number
%N	percent of rotational speed
t	target
ts	test
X	network input
Y	network output
Acronyms	
ANN	Artificial Neural Network
EGT	Exhaust Gas Temperature
RMSE	Root Mean Square Error
SVM	Support Vector Machine
Subscripts and Superscripts	
comp	compressor
f	fuel
o	output
test	related to network test
train	related to network training
turb	turbine

2. Aero-engine model and degradation analysis

2.1. Aero-engine description and model

In this work to test the effectiveness of the developed approach, a representative model gas turbine engine like Rolls Royce VIPER 632-43 aero engine is chosen, a turbojet that generates a static thrust of 17800 N at sea level. All the other detail are reported in [23]. The present study was carried out based on 3 samples flights denoted by Flight #1, Flight #2 and Flight #3 [23]. For each flight a total of 75 sample points referred to different flight conditions were selected, 25 for each phase: climb, cruise and descend. The data of these flights have been used for the training and testing process of the machine learning tools described in the next sections.

2.2. Test cases and engine data generation

It has been built a database of engine performance data coming from an healthy engine model. The synthetic data are generated with the combination of two software, *ONX* and *AEDSYS* [24]; the first one is used to model engine characteristics in design condition and this model has been validated on experimental data [23], the second one is able to test the modelled engine in different mission conditions, varying altitude, Mach and thrust request.

Most of the factors that deteriorate the gas turbine performance can be simulated by changing the health parameters of the engine components. Since fouling and erosion are considered among the main cause of performance deterioration, in this study, the effects of these degradations on compressor and gas turbine will be examined.

In order to test the approach three component degradation levels have been introduced used in the validated engine model; the first two cases have single component degradation only, and the third case has compressor and turbine degraded simultaneously. The simulated measurements are used as the input to the prediction model to test the system's capability in assessing the changing performance and health status of the engine.

2.3. Engine performance monitoring and degradation analysis

The approach of the study involves two different steps of the numerical tools can be noted. The first one runs as an engine model in order to achieve engine measurable data without any information about its health status; so this

Table 1. Input data set for engine performance model.

INPUT VECTOR	PARAMETERS SET
X_{train}	$(Alt\ Mach\ \%N)_{FLIGHT\ 1\text{-}2}$
Y_{train}	$(m_f\ EGT)_{FLIGHT\ 1\text{-}2}$
X_{test}	$(Alt\ Mach\ \%N)_{FLIGHT\ 3}$
Y_{test}	$(m_f\ EGT)_{FLIGHT\ 3}$

ANN or SVM model takes into account engine operating condition and gives as output engine measurable data. This first step can be considered an engine model able to monitor the engine performance. The data coming from the machine learning model are compared with the data coming from real engine acquisition system.

In a second phase, if the two data disagree, the ANN or SVM diagnostics model works to detect the degraded component, taking into account flight data and data from engine acquisition system and giving as output diagnostics information about components health state and helping about maintenance decisions.

3. Machine learning tools for gas turbine performance and health status estimation

In the first part of this section a brief description of the artificial neural network and support vector machine has been presented; then the test cases and relative scenarios are shown.

3.1 Artificial Neural Network

The neural network consists of a number of interconnected processing nodes called neurons, which are organized in a sequence of layers, including an input layer, a single intermediate hidden layer, and an output layer.

The input signals – of varying intensity and strength – feed through the neuron and combine to form a net input into another neuron. The output layer, equal to the number of dependent variables, is calculated by weight and bias associated with connections among neurons. The intermediate layer is connected to the input and output layers. Each neuron in the hidden and output layers receives the signals from all the neurons in a layer above it and then performs a weighted summation and transfer function of the inputs.

In particular a two-layer feed-forward network with sigmoid hidden neurons and linear output neurons was implemented. The network was trained with Bayesian regularization training algorithm function. The optimal number of hidden neurons and of the number of epochs was obtained carrying out a sensibility analysis based on the percent error between the target value and output values obtained by using neural networks with different numbers of hidden neurons and epochs. The best performance of the neural network was achieved with 5 hidden neurons and 2000 epochs for every simulates test case. For both the models the data of three flights need to be divided into training, validation, and test sets. The validation set was used to ensure that there was no overfitting in the final results. In detail for training and validation dataset have been used data from Flight#1 and Flight#2; the network testing has been performed on the data from Flight#3. In this manner we are able to quantify the tool efficiency using data "never seen before" by the network.

Table 2. Engine degradation level.

CONFIGURATION	Synthetic health state	η_{comp}	η_{turb}
HEALTHY	0	0.90	0.89
COMPRESSOR DEGRADATION	1	0.85	0.89
		0.80	
		0.77	
TURBINE DEGRADATION	2	0.90	0.84
			0.79
			0.76
COMPRESSOR & TURBINE DEGRADATION	3	0.85	0.84
		0.85	0.79
		0.80	0.84

3.2 Support Vector Machine

Support vector machines (SVMs) are a set of related supervised learning methods, applicable to both classification and regression. Originally the use was limited to linear two-class classification with margin, the minimal distance from the separating hyperplane to the nearest data points. SVM models look for the optimal separating hyperplane, where the margin is maximal. These points are called support vectors. The linear SVM can be extended to nonlinear one when first the problem is transformed into a feature space using a set of nonlinear basis functions.
Intuitively, the polynomial kernel looks not only at the given features of input samples to determine their similarity, but also combinations of these. In the context of regression analysis, such combinations are known as interaction features. An important advantage of the SVM is that it is not necessary to implement this transformation and to determine the separating hyperplane in the possibly very-high dimensional feature space, instead a kernel representation can be used, where the solution is written as a weighted sum of the values of certain kernel function evaluated at the support vectors [25]. More details are reported in [21].
For the ANN or SVM output estimation the Root Mean Square Error RMSE evaluated on the test data of each j-th output:

$$\left(RMSE = \sqrt{\frac{1}{n_{ts}} \sum_{i=1}^{n_{ts}} (t_i - y_i)^2} \right)_j \qquad \text{for } j=1,\ldots\ldots,n_o \tag{1}$$

where t_i are the target output and y_i the network output, n_{ts} the number of data used for test and n_o the number of model output. In our case n_{ts}= 75, the number of data of the Flight 3 and n_o = 2.

3.3 Simulation of engine performance

The first aim was to create a robust model that predicts performances in various flight conditions. In this way it's possible to create a database of expected values of the engine operative parameters at different operating conditions.
The input variables considered in the engine model are shown in Table 1. The letter X and Y are referred to net input and output respectively.
As previously described, experimental data from Flight#1 and Flight#2 have been used for the training process, experimental data from Flight#3 for testing the model.
The chosen dataset involves not only flight condition, namely Mach number and altitude, in the input vector but also rotational speed to give a information about the user power demand. The tool outputs (the values in the Y matrix) have been normalized respect the maximum value in order to allow the tool calculation in a controlled range 0-1.

3.4 ANN and SVM models for aero-engine health diagnostics

The model outputs, namely fuel mass flow rate and exhaust gas temperature, can be compared with the data from real engine acquisition system. If the two data are not in agreement the data from the engine acquisition system can be addressed into the diagnostics model to detect the degraded component.
The simulated scenarios are summarized in Table 2 where four health status scenarios can be noted. In correspondence of an healthy engine (synthetic health state equal to 0) the efficiency of the compressor and the turbine are equal to their nominal values. Then three different degraded scenarios are implemented for the single component and for both the components, each for its part with three degradation levels. In the two scenarios with the degradation of a single component, the efficiency of the other component is kept constant to its design value (synthetic health state equal to 1 for degraded compressor and 2 for degraded turbine). For the tool trained with the aim of identifying a synthetic engine health status the simulated dataset is summarized in Table 3; fuel mass flow rate and exhaust gas temperature are able to identify the engine health index [23] but in the chosen dataset we added respectively the Mach number to test the flight condition utility.

4. Results and Discussions

4.1 Performance analysis results

For the performance prediction, the two numerical tools involve flight conditions, in terms of altitude and Mach value linked to rotational speed in the input vector with as output engine performance in terms of fuel flow rate and exhaust gas temperature, as reported in Table 1. The test set gave an independent measure of how well the network

Table 3. Different data set for ANN and SVM engine health status diagnostics models.

INPUT VECTOR	**PARAMETERS**
	SET
$\mathbf{X_{train}}$	$\mathbf{(Mach\ m_f\ EGT)_{FLIGHT\ 1\text{-}2}}$
$\mathbf{Y_{train}}$	$\mathbf{(0\ 1\ 2\ 3)_{FLIGHT\ 1\text{-}2}}$
$\mathbf{X_{test}}$	$\mathbf{(Mach\ m_f\ EGT)_{FLIGHT\ 3}}$
$\mathbf{Y_{test}}$	$\mathbf{(0\ 1\ 2\ 3)_{FLIGHT\ 3}}$

can be expected to perform on data not used to train it. As said before Flight #1 and Flight #2 have been used for training. The accuracy level has been measured on the data from Flight #3, comparing fuel flow and EGT values coming from ANN and SVM output with the expected values. Fig. 1 shows the trend of the two physical quantities and reports the synthetic value of the associated RMSE. It's evident that both the models are able to predict well the engine performance. It's notable that the SVM model has a bit larger RMSE value than ANN model, particularly for the output values near the minimum, 0.25 for normalized fuel flow and 0.65 for normalized EGT. The trained and tested models can be used to create a database of expected values otherwise it can be run in real time to give the reference value for a specific set of altitude, Mach value and engine rotational speed.

4.2 Results of Engine Component Health Status Prediction

In this section a synthetic health state for the engine has been considered in order to predict the status of engine components, after a detected mismatch between the performance values coming from engine data acquisition system and the values of the same physical quantities coming from the engine model described in the previous section. With the help of the Table 2 that reports the health state conditions, we can assert if the engine is healthy (0), or if there is a trouble in the compressor (1), in the turbine (2) or in both these two components (3).

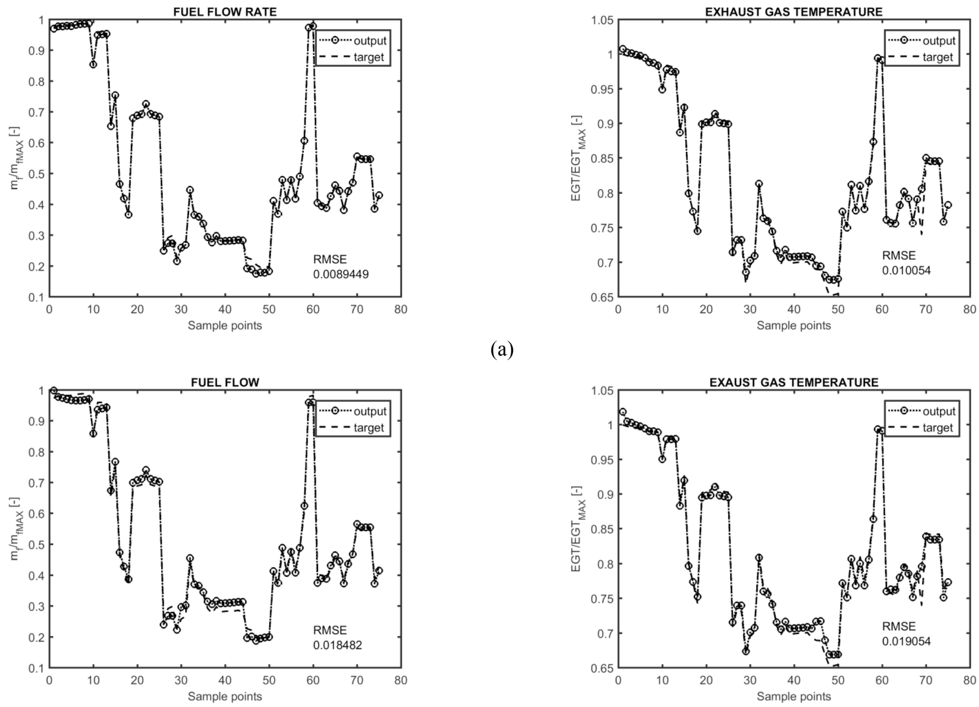
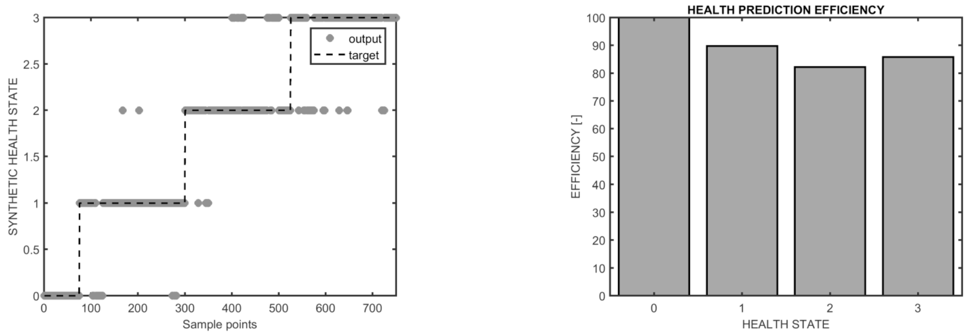
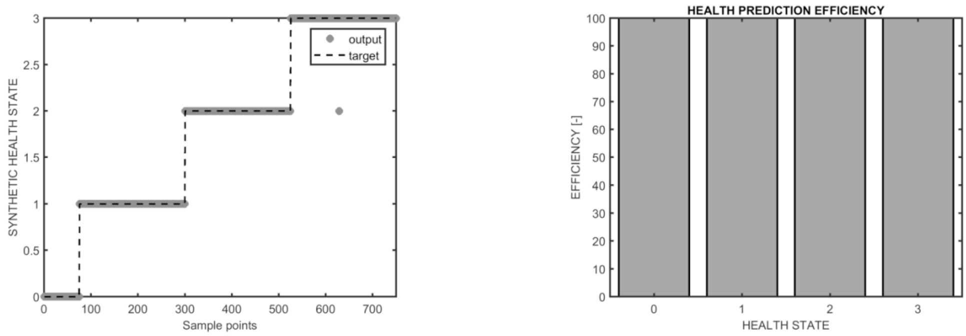


Fig. 1. . Performance prediction results for ANN model (a) and SVM (b).



(a)



(b)

Fig. 2. Engine synthetic health status prediction for ANN (a) and SVM (b).

We tested the performance of the dataset listed in Table 3, where we chose engine performance parameters as input and the previously described synthetic health state as output. The used dataset is a compromise between performance parameters, such as fuel flow rate and exhaust gas temperature, and flight parameters, such as Mach number. FigureFig. 2 shows the trend of the models output respect to the expected values and the efficiency of this forecast is depicted with histograms; in this case the tool efficiency is calculated counting the number of right values respect to the total values. In the efficiency histograms the four zones with a different health state code have been highlighted and separated in order to evaluate the model performance in every condition. In Fig. 2a the results for the ANN model and in Fig. 2b for SVM model are depicted.
Dividing the results in zones with different degraded scenarios it's detectable the component with major troubles but it's impossible to quantify its deterioration level giving us only an alert about the engine health condition.
The SVM models have been trained with different optimization function: linear, quadratic and cubic. Table 4 reports the performance for each available function. The performance are measured in terms of RMSE value for the model that predicts engine performance and in terms of accuracy for the model that classifies engine health status.
The quadratic learning function which shows the best results has been chosen for the SVM models. The high accuracy level (99.4%) is evident also in the graphs of Figure 4b. The SVM model with quadratic learning function has the best performance as classifier of the engine health status. The ANN model has very good performance for the healthy engine condition but there are some misleading prediction for the output conditions 1, 2 and 3.

Conclusions

This work aims to create a tool for monitoring aero-engine health status. Different machine learning techniques have been compared. Both ANN and SVM based models have shown very good results, in terms of engine performance parameters calculated from only few operational data; the very small computational time for this tools allows their use also in real-time condition. The engine model based on ANN is slightly better than the SVM based model probably because of the linearity between data used as input and output. The diagnostics models needed more time

and more attempts to find the right compromise between performance and operating parameters to use as input. For this purpose, SVM model has shown excellent performance, outperforming ANN as classifier tool.
As further development we want to create a tool able to calculate the analytic value of components efficiency.
The knowledge of the real engine health status can be crucial for maintenance and fleet management decisions. The long-term objective of the research will be a data-driven maintenance, which can be carried out with an innovative methodological analysis of the big data cluster from aero-engine system.

Table 4. SVM model training function performance.

TRAINING FUNCTION	RMSE [-]	ACCURACY [%]
Linear	**0.021528**	**97.5**
Quadratic	**0.018768**	**99.4**
Cubic	**0.0195437**	**98.9**

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